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Shifting ML value creation mechanisms: A process model of ML value creation

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A R T I C L E I N F O

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A B S T R A C T

Advancements in artificial intelligence (AI) technologies are rapidly changing the competitive landscape. In the search for an appropriate strategic response, firms are currently engaging in a large variety of AI projects. However, recent studies suggest that many companies are falling short in creating tangible business value through AI. As the current scientific body of knowledge lacks empirically-grounded research studies for explaining this phenomenon, we conducted an exploratory interview study focusing on 56 applications of machine learning (ML) in 29 different companies. Through an inductive qualitative analysis, we uncover three broad types and five subtypes of ML value creation mechanisms, identify necessary but not sufficient conditions for successfully leveraging them, and observe that organizations, in their efforts to create value, dynamically shift from one ML value creation mechanism to another by reconfiguring their ML applications (i.e., the shifting practice). We synthesize these findings into a process model of ML value creation, which illustrates how organizations engage in (resource) orchestration by shifting between ML value creation mechanisms as their capabilities evolve and business conditions change. Our model provides an alternative explanation for the current high failure rate of ML projects.

Introduction

Artificial intelligence (AI) holds the potential to reshape the corporate landscape, be it in the form of business models and corporate offerings (Fanti et al., 2020; Wiener et al., 2020), business processes (Ransbotham et al., 2017; Tarafdar et al., 2019), or the nature of work (Frank et al., 2019). Despite recent technological advances in AI technologies, their impact on economies and organizations has been modest so far (Brynjolfsson et al., 2017). The increasing diffusion of AI has not led to any measurable growth in productivity at the level of economies; in fact, the growth of the overall economy has declined over the past decade (Brynjolfsson et al., 2017). According to Brynjolfsson and colleagues (2017), likely explanations for this AI productivity paradox are organizational implementation and restructuring time lags. The full effects of AI will not be realized until companies develop and implement new complementary organizational capabilities that would allow them to mobilize and leverage AI resources and achieve their business objectives. This

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already points to a need for organizations to understand how to structure AI and other resources, bundle them into capabilities, and ultimately capitalize on these capabilities.

Research at the organizational level supports this proposition. Companies seem to struggle with realizing and sustaining value from AI initiatives (Brynjolfsson et al., 2017; Tarafdar et al., 2019). Many companies run only ad-hoc projects without developing organization-wide AI strategies or apply AI in just a single business process (Fountaine et al., 2019). Others go directly for “moonshot” projects (i.e., ambitious, exploratory, and ground-breaking endeavors) without any expectation of near-term profitability and without systematically evaluating where AI would create the most value (Davenport & Ronanki, 2018).

Both academic and practitioner-oriented discourses focus on the possibilities that AI offers (Coombs et al., 2020; Davenport & Ronanki, 2018; Shrestha et al., 2019), but fall short of uncovering the mechanisms that may produce the promised outcomes. So far, the academic discussion on AI value creation mechanisms centers around the choice between AI augmentation versus AI automation, otherwise known as the support-versus-replace debate (see Markus, 2017; Zuboff, 1985). Yet, we are currently lacking empirical research that analyzes how organizations decide about the level of augmentation/automation (Coombs et al., 2020), what kind of value organizations try to generate with AI (Lyytinen et al., 2020), and what organizational strategies they employ to pursue value from AI (Berente et al., 2021; Günther et al., 2017). We address the calls from both information systems (IS) (Coombs et al., 2020; Galliers et al., 2017; Markus, 2017; Rai et al., 2019) and management scholars (Raisch & Krakowski, 2020; von Krogh, 2018) to study how organizations pursue their value targets through AI applications.

From a technology perspective, there are two approaches to developing AI systems (Berente et al., 2021): the *rule-based approach*, also known as symbolic AI; and the *machine learning (ML) approach*, also known as the connectionist approach (Chollet, 2019; Legg & Hutter, 2007). While the rule-based approach played an important role in the early days of AI, since the resurgence of ML in the 1990s and the rise of deep learning in the 2010s, the learning approach is increasingly becoming the dominant approach to building AI systems (Berente et al., 2021; Haenlein & Kaplan, 2019). Therefore, in our study, we focus on the applications of ML and examine the mechanisms firms employ in trying to reach their value targets. Our work draws on theoretical foundations of the business value of data-intensive practices, especially big data analytics (BDA). More specifically, we use the research framework of Grover et al. (2018) on “value creation by big data analytics” and insights from resource orchestration literature as sensitizing devices. The framework highlights the importance of value creation mechanisms in the process of translating investments in IT infrastructure into business value. Value creation mechanisms represent “different ways to create value” (Grover et al. 2018, p. 400) using a technology and “indicate the fundamental source of value being pursued” (p. 401). In other words, value creation mechanisms describe the *way* to reach certain organizational goals (e.g., product and service innovation, business process improvement); whether this *goal* will eventually be reached (i.e., measurable business value is created) depends on several additional factors (e.g., the overall economic situation, competition in the industry, changing customer needs). Against this background, we investigate the following research question:

What are the value creation mechanisms that organizations employ to pursue their value targets through ML applications?

To answer the above research question, we carried out an exploratory interview study focusing on 56 applications of ML in 29 organizations. Our findings show that there are three different ML value creation mechanisms (with five subtypes) that organizations can employ to pursue their value targets. Each ML value creation mechanism represents a unique and fundamental source of value that organizations pursue. Next to that, we found that organizations sometimes shift from one value creation mechanism to another, within the same project, by rearranging their human-ML configurations. Finally, we identified necessary but not sufficient conditions for employing the different value creation mechanisms that provide explanations for the current high failure rate of ML projects. Based on these findings, we synthesize a process model of ML value creation, which illustrates how organizations engage in (resource) orchestration by shifting between ML value creation mechanisms as their capabilities evolve and/or business conditions change. In this respect, our study contributes to the current literature on designing and implementing strategies in the context of ML systems by linking capabilities, managerial action, and value creation mechanisms in dynamic organizational environments. Furthermore, our findings contribute to data-intensive work studies showing the critical role of data scientists in orchestration activities, as they pursue creating and sustaining value through ML applications.

The remainder of this paper is structured as follows: First, we provide the background of our study. Next, we present our research method, followed by the presentation and discussion of our findings. We conclude by summarizing the study’s limitations and contributions.

Background

As the objective of this study is to identify value creation mechanisms that explain how organizations can reach their value targets with ML, rather than any digital technology, we focus our literature review on how ML applications can be used for pursuing organizational goals. In doing this, we first summarize the characteristics of ML technology and how it is currently used in organizational settings. Next, we unpack the notion of mechanisms, what it means to identify value creation mechanisms in organizations, and how they are grounded in the resource-based view of the firm—more specifically, in the idea of resource orchestration.

ML technology and its organizational uses

Advances in ML technology have revitalized interest in AI research. Recent breakthroughs in the field of ML (e.g., deep neural networks) have been driven by dramatic increases in the availability of digital data and computing resources (Dean et al., 2018). Indeed, the effective use of ML would not be possible without foundational data-intensive technologies such as big data analytics

(BDA). Yet, ML and BDA are distinct phenomena with essential conceptual differences. BDA stands in a long tradition of technologies[1], all of which were meant to "informate" (Zuboff, 1985); that is, to provide decision makers with relevant information (Abbasi et al., 2016; Debortoli et al., 2014; Grover et al., 2018; Kitchin & McArdle, 2016; Müller et al., 2018). The vision of the field of ML, on the other hand, is to develop intelligent machines that are able to learn how to perform complex cognitive tasks without being explicitly programmed to do so (Samuel, 1959). This vision goes beyond mere decision support; instead, it highlights the ambition to create artificial agents that are able to automate cognitive tasks which were formerly reserved for humans, and learn how to do this better over time (Rai et al., 2019; Schuetz & Venkatesh, 2020; Sturm et al., 2021). Currently, we are still far away from this vision. The learning capacity of today's ML systems is limited to finding ways to optimize an objective function defined by its designer; in other words, today's ML systems cannot set or modify their own learning goals (Aleksander, 2017). So, while ML and BDA are related technologies (e.g., ML uses the data provided by BDA), there are important differences in how these technologies contribute to organizational goals (i.e., informate human decision makers vs. automate cognitive tasks).

In fact, seen as a new generation of IS that can learn and act autonomously, ML-based AI systems constitute a new form of agency (Ågerfalk, 2020). Following this notion, several scholars have drawn up new research agendas to understand the implications of AI and underlying technologies for individuals, businesses, and societies (Ågerfalk, 2020; Baird & Maruping, 2021; Coombs et al., 2020; Lyytinen et al., 2020; Schuetz & Venkatesh, 2020). Regarding the value contribution of ML applications in organizations, we identify three main streams of research.

The first stream covers conceptual work around the automation possibilities of AI technologies, including ML (Acemoglu & Restrepo, 2021; Agrawal et al., 2018; Coombs et al., 2020; Makridakis, 2017; Tarafdar et al., 2019). In these studies, in line with the economic logic, the contribution of AI to organizational goals is often associated with automation (Zuboff, 1985).

In parallel to the rather technology-oriented view of AI as an automation technology, a second research stream has evolved that highlights the use of AI and ML-based applications for augmentation purposes (i.e., ameliorate—instead of substitute—human work with AI). This research focuses on the organizational embedding of ML technology and expands on the effective combination of human-ML configurations (Baird & Maruping, 2021; Grønsund & Aanestad, 2020; Shrestha et al., 2019; van den Broek et al., 2021). Combining these first two views suggests that the value contribution of ML applications in organizations is not as black and white as often portrayed. Hence, organizations need to engage in applications of ML that both augment and automate human capabilities in order to "achieve complementarities that benefit business and society" (Raisch & Krakowski, 2020, p. 192). This requires that organizations continuously realign work practices, organizational models, and stakeholder interests in order to sustain these complementarities (Grønsund & Aanestad, 2020; Günther et al., 2017; Lebovitz et al., 2021; Markus, 2017; van den Broek et al., 2021). In relation to these complementarities, researchers have started to develop and explore concepts such AI readiness and AI capability (Jöhnk et al., 2021; Mikalef & Gupta, 2021; Pumplun et al., 2019) to characterize organizational abilities to deploy and use AI in ways that add value. These studies, however, are either on a conceptual level describing and defining these new notions or they are variance studies that provide evidence for, or quantify, AI capability's impact on organizational performance. These are important steps in understanding if and what are the AI readiness factors and AI resources that enable organizations to create business value. Yet, we still lack an understanding of the different ways organizations bundle, mobilize, configure, and reconfigure these AI resources and capabilities into AI applications in order to pursue organizational objectives.

Finally, a third debate has emerged on the actors that manage ML scoping, development, and deployment in organizations. While managers are acknowledged and expected to "make all key decisions about AI" (Berente et al., 2021, p. 1434), they also face a variety of new challenges, many of which are of a technical nature (Berente et al., 2021). As managers struggle with understanding AI technologies and how they work (Davenport & Ronanki, 2018; Li et al., 2021), *data scientists* appear to take a more prominent role as agents of change. Organizational field studies on human-ML configurations provide evidence of the important role data scientists play not only in setting up ML models but also in many managerial activities in ML projects (Grønsund & Aanestad, 2020; Pachidi et al., 2021; van den Broek et al., 2021). It appears that "the role of the data scientist is to be the value creator—the bridge between statistician/computer engineer/etc. and key decision makers'' (Vaast & Pinsonneault, 2021, p. 1095). As such, they have emerged as key actors in leveraging ML applications for organizational value creation (see Joshi et al. (2021) for examples).

Value creation mechanisms and the resource orchestration view

From a managerial perspective, ML technology is a new technology that organizations can employ to achieve organizational goals. That is, ML technology enables new value creation mechanisms through which organizations can pursue their organizational goals. Following this, we continue our review with unpacking the notion of value creation mechanisms and their grounding in the resource orchestration perspective of the resource-based view of the firm.

According to Anderson et al. (2006), a focus on organizational mechanisms enables one to "move beyond thinking about individual variables and the specific links between them to considering the bigger picture of *action* in its entirety" (p. 103). This means that the important elements of organizations are not the components (e.g., resources and capabilities) themselves, but rather the cogs and gears that enable the translation from moving one component into the movement of another component. Specifically, as Hernes (1998) points out, mechanisms are about "the wheelwork or agency by which an effect is produced. In this way, mechanisms do not merely address what happened, but also how it happened" (p. 74). Mechanisms, however, do not apply or always work no matter what. There

[1] From the emergence of the first decision support systems in the 1960s to the wide-spread diffusion of enterprise-wide business intelligence platforms in the 1990s, later continued to business intelligence & Analytics (see Chen et al., 2012 for a historical overview).

are boundary conditions that become explicit as researchers identify mechanisms. The main task of the researcher then becomes to'identify' mechanisms and to establish under which conditions they'come into being','fail to operate', and so on (Merton & Merton, 1968).

Together with resource-based theory, dynamic capabilities, and resource orchestration are theoretical concepts often used to investigate value creation mechanisms in organizations. Resource-based theory emphasizes the role of firm resources as the basis for creating business value and achieving competitive advantage. In this way, companies can identify, acquire, and develop the necessary assets, capabilities, and competencies that would provide them the potential to deliver superior competitive advantages. While the resource-based view is still a very useful framework for managers, it emphasizes resource possession and selection (i.e, the characteristics of resources that influence performance through competitive advantage), rather than resource renewal or managerial action that appear especially critical in dynamic business environments (Sirmon et al., 2011; Teece et al., 1997; Teece et al., 2007). To address these limitations, new concepts have emerged, such as dynamic capabilities (Teece et al., 1997) and resource orchestration (Sirmon et al., 2011).

Dynamic capabilities encapsulate the evolutionary nature of resources in organizations (Teece et al., 1997; Teece et al., 2007; Pavlou & El Sawy, 2006; Pavlou & El Sawy, 2011; Zahra & George, 2002) and emphasize “the firm’s ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments” (Teece et al., 1997, p. 516). On the other hand, the resource orchestration view emphasizes process-oriented managerial actions that are involved in value creation processes (Sirmon et al., 2011). The resource orchestration view points out that strategic resources do not appear by magic but are rather developed (Chadwick et al., 2015), given that firms do not inherently know how to leverage resources to create value (Ndofor et al., 2011). Therefore, managers usually need to be actively involved in orchestrating resources for reaching their goals (Chadwick et al., 2015). Hence, the resource orchestration view focuses on managers’ actions to effectively structure, bundle, and leverage firm resources as they are critical to achieve not only organizational goals but also resource-based competitive advantage.

While extant literature on resource orchestration recognizes that there are multiple levels of management in companies, so far studies have tended to focus on top-level managers (Chadwick et al., 2015; Holcomb et al., 2009; Sirmon et al., 2008). The existing literature suggests that top-level managers direct the synchronization of the firm’s resource orchestration in a top-down process of strategic initiatives. In bottom-up and bidirectional approaches, however, middle-level managers are often more instrumental in synchronizing a firm’s resource orchestration efforts (Sirmon et al., 2011).

From the above insights, we understand value creation mechanisms as ways of orchestrating resources and capabilities to pursue value targets. Furthermore, we also understand that both top-level and middle-level managers play an active role in orchestrating resources. Top-level managers set value targets. Middle-level managers are the value creators by actively pursuing the value targets through mobilizing and leveraging value creation mechanisms.

Research on value creation mechanisms in IS

Several IS specific value creation models were developed grounded on the resource-based view (e.g., Kohli & Grover, 2008; Melville et al., 2004; Soh & Markus, 1995), highlighting the main components (e.g., resources, assets, capabilities, applications) and the fact that they need to undergo transformation processes for value to be created. More recently, Grover et al. (2018) proposed a value creation framework for BDA technologies by integrating key constructs from Soh & Markus (1995) and Melville (2004) into capability building and capability realization processes using the general framing of dynamic capabilities. The framework of Grover et al. (2018) emphasizes the role of value creation mechanisms as enablers for the transformation of capabilities into value targets. Value creation mechanisms indicate the fundamental source of value being pursued by specific technologies. Grover et al. (2018) consider the mechanisms underlying value creation of BDA practices as critical for organizations to achieve their value targets. Yet, there is no indication of how the capabilities for these mechanisms are combined when pursuing the value target, nor is there any explanation of who performs this work in organizations.

To the best of our knowledge, the literature lacks a comprehensive overview of ML value creation mechanisms. Previous studies have identified and confirmed value creation mechanisms for BDA technologies (Grover et al., 2018; Hopf et al., 2022; Zeng & Glaister,

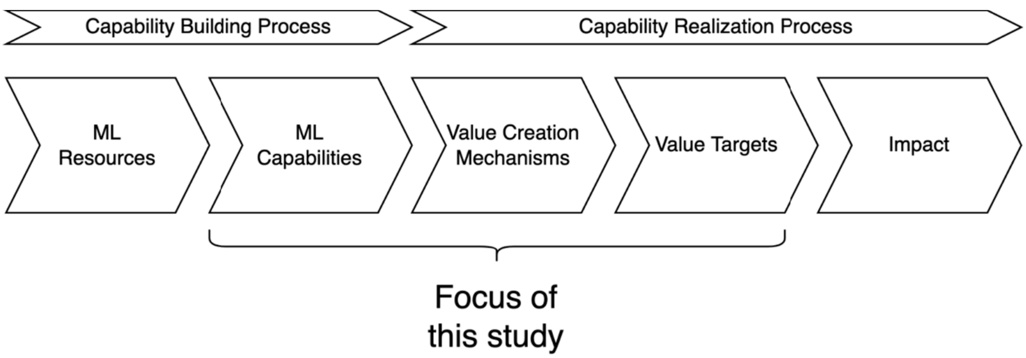

Fig. 1. Positioning of this study.

2018), such as "democratize data," "contextualize data," "experiment with data," and "execute data insights." Yet, as we have argued earlier, because BDA pursues a different organizational goal than ML, one cannot simply generalize or transfer BDA value creation mechanisms to the context of ML. Hence, identifying ML-specific value creation mechanisms promises to allow new insights into how ML resources and capabilities are combined to achieve respective value targets.

Motivated by the practical need to understand the mechanisms of ML value creation mechanisms in organizations and given the aforementioned theoretical gap, our study empirically explores the mechanisms of how organizations pursue their value targets through ML. Viewing ML value creation mechanisms through a resource orchestration lens means looking for ways that resources and capabilities are bundled, mobilized, configured, and reconfigured into ML applications in order to pursue specific value targets. We explicate boundary conditions and managerial decision options for value creation mechanisms. We illustrate the goal of our study within the existing theoretical framing in Fig. 1.

Method

We chose an exploratory and qualitative research design in which we conducted 40 semi-structured interviews with data scientists and managers who are involved in the development of ML applications. Below, we describe our study design, data collection, and analysis in detail.

Study design

Following the framework of Grover et al. (2018), we pursued a process perspective to investigate ML value creation in organizations and thoroughly examine the value creation mechanisms that are existent in organizations. For that, we selected to interview 40 data scientists of which seven had grown to a managerial position from a data science background (they are data science team leads or C-level representatives of small to medium-sized data analytics and ML service providers; most of them have a PhD). As indicated in the literature review, data scientists take over many managerial activities and decisions when it comes to ML applications. For example, they have "a role that demands more responsibility and a deeper sense of accountability" than statisticians or pure technical employees (Vaast & Pinsonneault, 2021, p. 1095), they decide over the inclusion and exclusion of domain experts in ML model development (van den Broek et al., 2021), and they switch between roles of augmenting and altering ML models (Grønsund & Aanestad, 2020). Based on their involvement in managerial activities, we view data scientists as active pursuers of ML value targets and key actors in leveraging the ML value creation mechanisms, and therefore a strong foundation for our study. The hybrid technical and business nature of their profession and their involvement throughout the lifecycle (Hummer et al., 2019) of ML projects gives them a holistic view on ML and its application in organizations (Davenport & Patil, 2012; Plastino & Purdy, 2018; van der Aalst, 2014) and makes them critical informants of how organizations achieve value targets through ML applications. By interviewing them, we gained an inside, bottom-up view into how ML applications are leveraged to pursue value targets (Plastino & Purdy, 2018)—a view we believe is lacking currently in the IS literature. Following Gioia (2013), we treated these "informants" as "knowledgeable agents," giving them an "extraordinary voice" (p. 26). Practically, this meant that we assumed that our informants "know what they are trying to do and can explain their thoughts, intentions, and actions" (Gioia et al., 2013, p. 17).

Data collection

We collected our empirical data between October 2018 and March 2020. In this period, we interviewed 40 data scientists from 29 companies about their involvement in 56 corporate applications of ML (ongoing projects and deployed systems).

Sampling strategy

In exploring the breadth and depth of the phenomenon, we followed a maximum variation strategy for purposeful sampling, which helped us to capture and describe mechanisms of ML value creation that cut across a great deal of variation (Patton, 2002, p. 234f). The organizations for which the interview partners worked covered six large (above 1,000 employees), sixteen medium-sized (between 15 and 1,000 employees), and seven small companies (below 15 employees). The companies belonged to a variety of industries (e.g., retailing, mechanical engineering, energy, banking and finance, robotics, IT consulting, data analytics vendors, transportation, media, pharma, foods and beverages, public sector). They were located mainly in Germany and Denmark, but also in other European countries, the U.S., and Singapore. Fourteen of them were operating globally. The interview partners had between several months to up to seven years of job experience in their current position. Some 21% of our interview partners were female. We provide full lists of the interviews and analyzed projects—together with descriptive information on the interviews, the investigated projects, and the companies—in the appendix (projects in Table A.1 and interviews in Table A.2).

We continued to conduct interviews until we found a point of redundancy in the mechanisms identified and further data collection did not add any new mechanisms (Corbin & Strauss, 2015; Lincoln & Guba, 1986, p. 203; Patton, 2002, p. 246). This manifested in our observation that the identified types of ML value creation (and subtypes, see next section) did not change in the last quarter of interviews of our study.

Structure and contents of the interviews

The retrospective accounts of our interviewees constituted the main data source for our research and theorizing process. The interviews followed an interview guide that we flexibly adjusted over time, driven by the accounts of the informants (Gioia et al., 2013) and the ongoing coding and theorizing process that we carried out with the help of a coding logbook. The overall structure of the interview guide (given in full in Appendix B) was, however, stable over time. We asked the informants about concrete ML projects in which they were involved in the past, or at the moment of the interview, thereby grounding the interview in participants' own experiences. This helped to keep the interviews rooted in actual events and settings, and reduced the risk of the conversation "spiraling into abstractions, generalities, and cultural scripts" (Schultze & Avital, 2011, p. 5). In some cases, we reached back out to informants of earlier interviews to ask about concepts that were arising from later interviews (Gioia et al., 2013).

Given the process perspective on ML value creation, which our chosen conceptualization (Grover et al., 2018) is based on, we used the typical steps of ML projects according to well-known project process models for ML and data analytics (Fayyad et al., 1996; Hummer et al., 2019; Sharma et al., 2014; Shearer, 2000; Thiess & Müller, 2018). In particular, we asked the informants how they approached and experienced each stage of this process (business problems to data, data to insight, insight to decisions, decisions to actions, and actions to value targets), what difficulties they faced in each stage, and which practices they used to achieve their value targets. The process steps proved to be useful for structuring our interviews. Still, the interviews remained open to probing into informant responses when they initiated a new area of inquiry.

Our technical background and experience in ML technology allowed us to go into the necessary depth of the domain with the interview partners, so that we understood how the projects were embedded in the organizational context and which ML technologies were used. The recorded interviews have a mean duration of 48.5 min (12 min standard deviation). Occasionally, we considered the company website in addition, as a means of researching metadata about the company or validating information provided in the interview.

To gather data about the value contribution of each investigated ML project, we opted—in accordance with the value creation framework of Grover et al. (2018)—to ask our informants for concrete value targets of each project. An (economic) impact assessment of the investigated projects under study would not have been feasible in our study. Such impacts are generally hard to measure and would require a longitudinal quantitative investigation, which was not and could not be achieved in a qualitative research design (Brynjolfsson et al., 2017; Müller et al., 2018; Schryen, 2013). Instead, to help interviewees think about the value targets, we used terms like "achievement," "contribution," or "success" and we asked what they were trying to or expected to achieve through the ML applications. We categorized the reported value targets based on categories of previous work (Elia et al., 2020; Gregor et al., 2006) and listed the specific value targets of each project in Table A.1.

Most of the interviews were conducted in English (23 out of 40), the rest in German. We analyzed the interviews in their original language and translated original quotes into English, when necessary, to include them in this paper for an international audience.

Data analysis

We recorded all interviews and transcribed them verbatim, which resulted in more than 600 pages of original text. Due to the exploratory nature of our research question, we applied an open coding approach to identify relevant and interesting chunks of data.

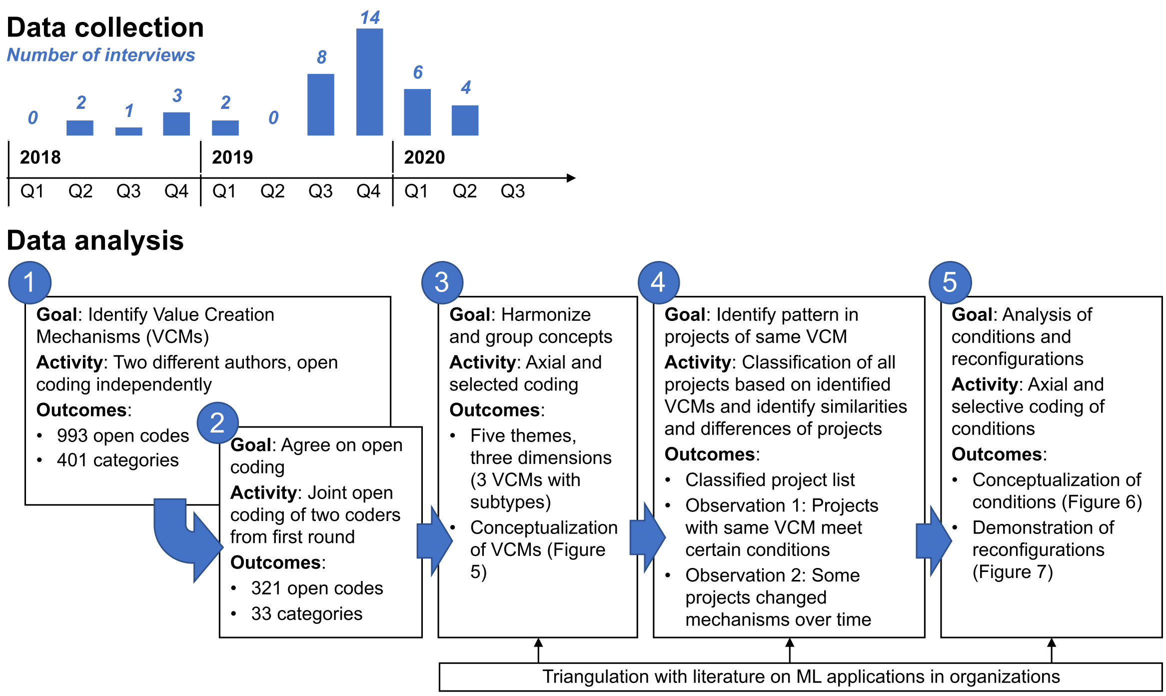

Fig. 2. Overview of the data collection and analysis approach.

Our data analysis procedure is illustrated in Fig. 2. We used MAXQDA software to analyze all collected data (interview and focus group meeting transcripts, written feedback).

The initial round of coding was done independently by two of the authors (Step 1 in Fig. 2), who tried to stay close to the words and phrases of the informants. This led to a large amount of open codes (Gioia et al., 2013). When disagreements emerged on open coding or their categories, the two researchers first went back to the raw data, discussed their interpretations, and tried to reach a collective interpretation. If an agreement on interpretation was not reached, the researchers engaged the help of the other researchers. After an agreement between the two initial coders (Step 2 in Fig. 2), all authors discussed the large number of data-driven open codes and used their experience and knowledge of relevant theory to make sense of the emerging concepts. In an iterative procedure of axial coding, we identified broader themes (Step 3 in Fig. 2). In a selective coding step, we integrated categories of organized data from axial coding to overarching theoretical dimensions: i.e., the value creation mechanisms (Gioia et al., 2013), as illustrated in Figs. 3 and 4. The full lists of open codes (with indicative quotes), themes, and dimensions are listed in the appendix in Table A.3 and Table A.4. Following an inductive approach, we tried not to force the emerging concepts into frames of pre-existing theory.

Through an iterative analysis, the themes and dimensions in relation to different mechanisms of creating value with ML and their characteristics emerged as "transparently observable" (Eisenhardt, 1989, p. 537). The first rounds of analysis resulted in three unique *ML value creation mechanisms*, which we refined in further rounds of analysis and coding until we reached a point of theoretical saturation, in which no conceptual deviations remained (Glaser & Strauss, 1967). This point of theoretical saturation (appearing often in the last quarter of interviews) was also the reason why we stopped collecting new interviews. Frameworks and concepts from existing literature supported this iterative data analysis process. In particular, we used the resource orchestration view and the BDA value creation framework by Grover et al. (2018) as an analytical lens and vocabulary for our theorizing process.

Once the emerging ML value creation mechanisms were sufficiently stable, we re-analyzed the data again through the lens of the emerging theory (step 4 in Fig. 2); that is, we classified all projects according to their value creation mechanisms (see Table A.1). This led us to uncover that the projects pursuing the same value creation type have certain *conditions* to be fulfilled to pursue their value targets. In addition, we found that, over the lifecycle of ML applications, projects often did not follow only one mechanism of value creation. Rather, some organizations reconfigured their ML applications in order to shift to a different value creation mechanism. These *reconfigurations* eventually became the focus of our final round of data analysis (step 5 in Fig. 2), in which we could substantiate the changing conditions that triggered the reconfiguration.

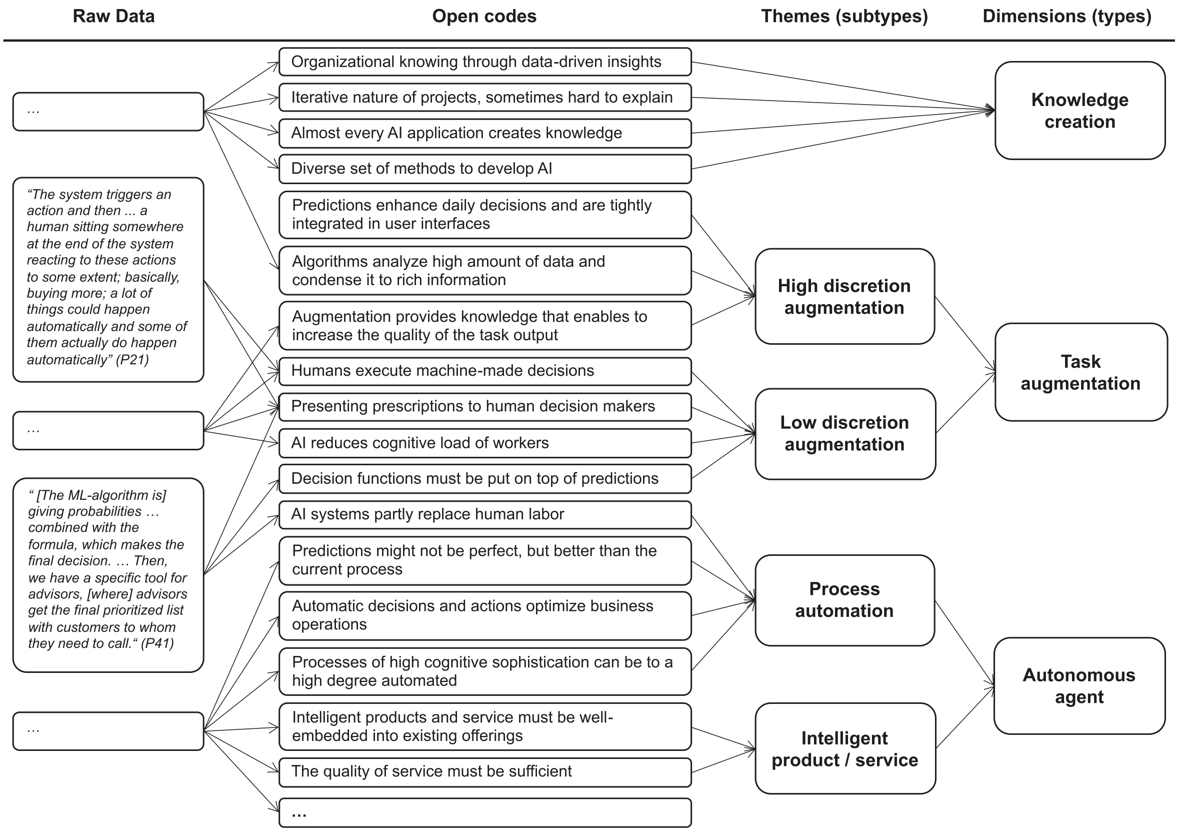

Fig. 3. From raw data over open codes to themes and dimensions (value creation mechanisms).

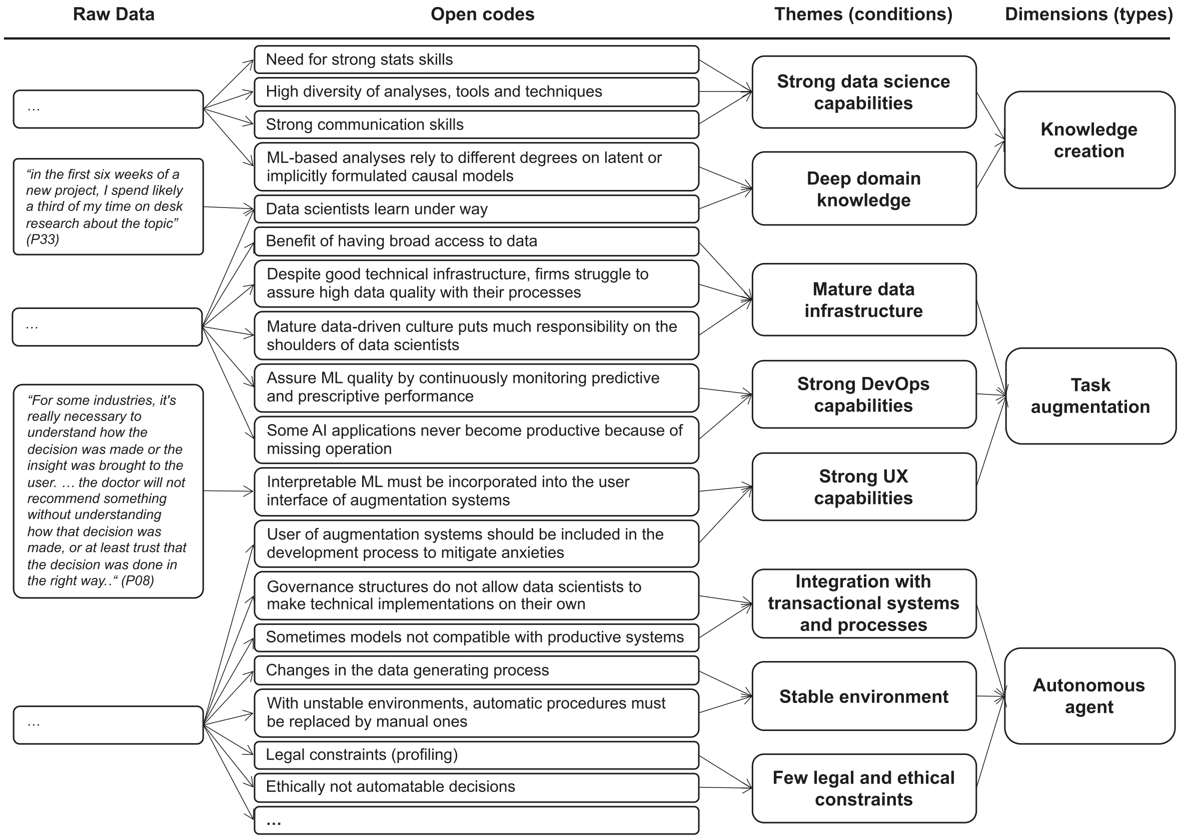

Fig. 4. Open codes, themes and dimensions for conditions.

Findings

This section describes the results of our empirical analysis. We identify three distinct ML value creation mechanisms, link them with their primary value targets, and describe the nature of each mechanism in detail using a common set of attributes. Thereafter, we exemplify how companies sometimes reconfigure their ML applications in reaction to changed internal or external conditions and, thereby, shift between different value creation mechanisms. We synthesize these rich findings into a process model for ML value

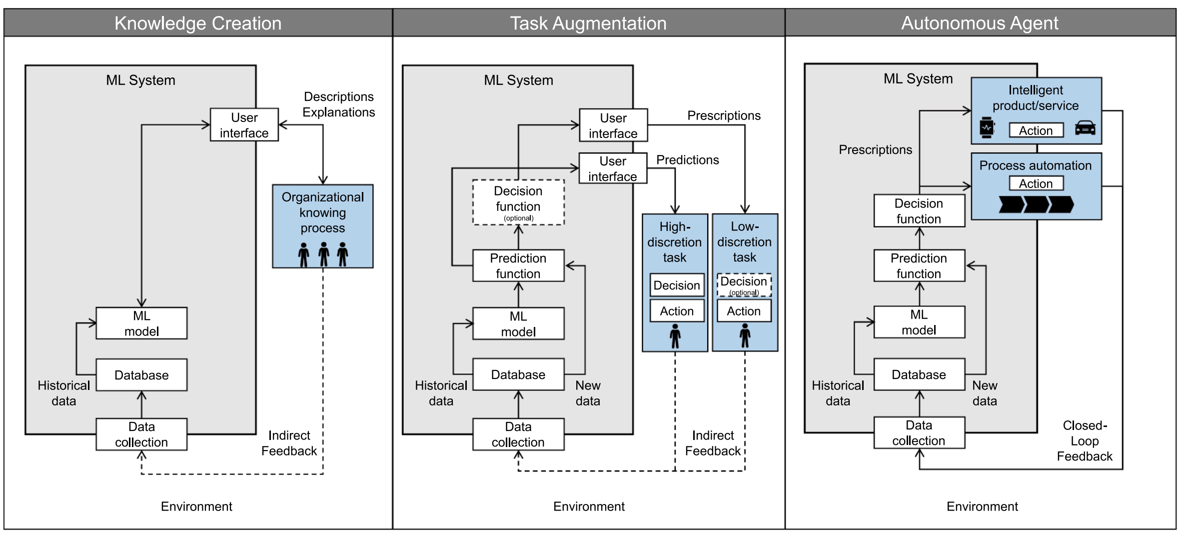

Fig. 5. Similarities and differences between knowledge creation, task augmentation, and autonomous agent mechanisms.

creation in organizational settings.

ML value creation mechanisms

In general, value creation mechanisms describe the way organizations intend to achieve certain value targets (Grover et al., 2018). In the context of ML, we found three broad value creation mechanisms and five subtypes within those. Fig. 5 gives an overview of the technical similarities and differences between the three ML value creation mechanisms. In all cases, we have an ML system that operates within an environment by collecting data from and returning information to that environment.

The value creation mechanisms differ in three main aspects: First, how tight this feedback loop is (from indirect to closed-loop); second, what kind of output the ML system generates (ranging from descriptions to prescriptions); and third, the division of labor between ML systems and human decision makers. The division of labor ranges from a clear focus on human agency in the case of the knowledge creation mechanism, to almost full algorithmic automation in the case of the autonomous agent mechanism. It also goes hand in hand with a varying amount of information processing through the ML system.

In the case of the knowledge creation mechanism, the ML system merely produces models which provide descriptions and explanations for organizational knowing processes. Task augmentation systems, in contrast, are equipped with prediction and decision functions on top of models. These functions generate predictions or prescriptions, respectively. Moreover, autonomous agents go beyond decision-making and actually perform—based on algorithmic prescriptions—real actions in the environment. Table 1 (on page 27) provides a structured summary of further differentiating characteristics for the value creation mechanisms. More details are available in the Tables A.3 and A.4 in the appendix, where we compiled an extensive listing of quotes from the interviews to further illustrate these mechanisms.

ML value creation mechanism 1: Knowledge creation

The first group of ML applications we identified pursued the value target of organizational knowledge creation. More specifically, 24 of 56 applications we studied had the goal of supporting humans in discovering new knowledge by providing them with ML-based tools for inductively identifying trends and patterns in historical data (see left part of Fig. 5). These knowledge creation systems are not independent agents. Rather, they are tools that are used by organizational decision makers—just as scientists use instruments like microscopes or telescopes in their research. We found that these systems often supported rather strategic decision-making processes (e.g., data-driven customer segmentation for market research, root-cause analysis for delivery shortages). We further found that these applications of ML rarely ended directly in the implementation of productive IT systems and instead focused on prototypes, or reports that have a relatively low technical maturity, without interactive user interfaces. However, project execution was frequently inefficient due to the ad-hoc nature of these projects and the fact that the analysis outputs were not used in a clearly defined downstream decision-making task, but rather mobilized as inputs for strategic decisions. Hence, these projects resembled more data-intensive research projects than classical IT projects. They included one-time, typically ad-hoc, analyses of historical data to generate exploratory and explanatory knowledge by modeling patterns and trends related to strategic decisions. Overall, we could observe a tendency to apply transparent models instead of highly complex black box algorithms, as the goal of these projects was to explore relationships between variables or to test hypotheses. Many interviewees described the objective of these projects as "identifying the drivers of the [data generating] process," which then allow the creation of an understanding of existing phenomena and support the development of new concepts and ideas. These projects typically create knowledge that describes or explains phenomena for whole (sub-)populations (e.g., customer groups) rather than predicting events on an individual level (e.g., a single customer). For example, describing a customer churn analysis in the energy industry, one of our interviews explained: "In my opinion, what generates the most impact are the factors

Table 1
Attributes of the ML value creation mechanisms.

	Knowledge creation (ML value creation mechanism 1)	**Task augmentation (ML value creation mechanism 2)**	**Autonomous agents (ML value creation mechanism 3)**
Subtypes	–	Low- and high-discretion (decision-making) tasks	Process automation, Intelligent products and services
Value targets	Organizational knowing	More effective (faster or better) decision-making	Increased productivity, novel value offerings
Required capabilities and environmental factors	Strong data science capabilities, deep domain knowledge	Mature data infrastructure, strong DevOps, user experience (UX) capabilities	Integration with transactional systems and processes, stable environment, few legal and ethical constraints
Output	Descriptions (patterns, trends) and explanations (tested hypotheses)	Predictions (probabilities, scores, forecasts, etc.) and prescriptions (recommendations, instructions)	Prescriptions (instructions)
Deployed algorithms and models	Unsupervised ML, causal inference, simulation	Supervised ML and optimization	Supervised ML and optimization
Decision maker	Human	Human (at least in the loop)	Machine
Action taker	Human	Human or machine	Machine
Level of decision-making	Strategic and tactical	Tactical and operational	Operational

influencing customer behavior that our models spit out. They serve as a basis for discussion in the company about how one might develop new concepts." (Translated; P03: Customer churn modeling). Such data-driven discoveries are usually represented as parameters of a statistical model that, for example, explains customer churn. In the above-mentioned project, for instance, a pattern was identified that for a one-unit increase in customer spending, the likelihood that customer churn decreases by a certain percentage point.

ML value creation mechanism 2: Task augmentation

The second group of ML applications we identified (18 of 56 applications) pursued the value target of more effective decision-making by enabling humans to either make better or faster decisions. In contrast to knowledge creation systems, these ML-based systems, which we named task augmentation systems, focus on more structured decisions that occur in higher frequency and volume. We found that task augmentation projects are mostly concerned with implementing ML-based systems into production environments to augment human capabilities and support them in their everyday work tasks. Here, humans still remain the final decision makers in the end, but they receive advice or instructions originating from a predictive or prescriptive ML model and optional decision function. Hence, the underlying value creation mechanism is to augment the limited information processing capabilities of humans with the superhuman capabilities of ML, hence combining and leveraging human capabilities and ML resources for targeting more effective or efficient decision-making.

We identified two subtypes of the task augmentation mechanism: applications that leave high or low discretion for the human decision maker (i.e., the user of the system).

High-discretion task augmentation. These applications of ML support decision-making in ways that leave large parts of the final judgment and choices to the discretion of their users. This is done, for example, by displaying a set of predictions or recommendations, from which the user can select one or decide to ignore them completely. The sales department of a pharmaceutical company, for example, has enriched its customer relationship management (CRM) system with color-coded ratings that indicate the preferred communication channel for office-based physicians. Leveraging these predictions, but also the experience and personal relationships of the sales agents, they can choose the most promising channel for contacting the client. Another example is a digital parking assistant, which one of our interviewees described as follows: "That's ultimately a tool with a dashboard that shows how likely it is that a parking space will be available. Then the drivers can decide whether they use the parking space or not." (Translated, P34: Parking area demand forecast).

Low-discretion task augmentation. These applications of ML allow users only little influence on the final decisions made. For example, an energy retailer implemented a task augmentation system in its call center, which dynamically instructs agents what questions to ask and in which order. The agents have little influence on how to conduct the conversation, as they continuously receive prescriptions by the system on how to act and have only a few seconds to think about questions and answers. In the case of such low-discretion augmentation systems, the main role of the user is not to be a decision maker, but rather to be an actuator that can intervene and overrule the system when exceptions or anomalies occur. We found that tasks that are supported by such low-discretion systems could be fully automated in theory (including implementation of the chosen actions), because users mostly follow the instructions of the system. However, in practice, the final decision remained with the human due to technical, ethical, legal, or risk-related concerns.

In contrast to high-discretion augmentation systems, which usually make predictions, low-discretion augmentation systems go one step further and generate prescriptions. They do so through decision functions that perform automatic selection of a final and often mathematically optimal set of courses of actions out of several evaluated alternatives. Frequently, optimization algorithms (e.g., linear programming) or simple heuristics like "take the alternative with the highest score" are applied. For example, in the call center system mentioned earlier, the task augmentation system only instructs agents to ask questions about customer satisfaction at the end of a call, if the estimated churn probability for a given customer exceeds a certain threshold. Therefore, the call center agent has almost no discretion in this case.

ML value creation mechanism 3: Autonomous agent

The third ML value creation mechanism we identified was concerned with automation. The primary value target of the underlying projects (14 of 56) was to use automation to either increase productivity, by substituting human labor through ML-based agents, or to enable new value propositions, by offering smarter products and services. In contrast to knowledge creation and augmentation systems, autonomous agents make decisions and implement actions without a human in the loop (see right part of Fig. 5). In order to achieve this, they typically combine supervised ML models with decision functions to automatically choose a mathematically optimal sequence of actions.

We identified two subtypes of ML-based autonomous agents. ML can improve, on the one hand, the efficiency of (existing) business processes by reducing time and resources needed for process execution. We name these applications of ML *process automation*. On the other hand, ML can be an integral part of an intelligent—often called smart—product or service. We label these applications of ML as *intelligent products and services*.

Process automation. Here, the ML system executes internal business processes to make them more efficient. A representative example for this type of application is the automated placement of advertisement banners at websites, operated by a multinational jewelry retailer we interviewed. In the past, external agencies or internal advertisement professionals decided which banner to place at which website and when. Today, they have automated this process end-to-end; the ML system is provided with a budget to spend and not only makes all placement decisions autonomously, but also executes all required actions. Customers, however, do not even have to realize that ML is at work. A service provider that offers a media summary for companies (e.g., all mentions of the company name in important magazines), for example, had automated its process with ML, but the value proposition that the company delivered to customers remained unchanged (i.e., a standardized email, PDF report).

Intelligent products and services. ML applications are also used to create new intelligent products and services that can be offered directly to customers. The offers may be sold as separate goods (e.g., smart devices, apps, or paid services) or are intended to increase the service level of existing offers (e.g., to improve customer service). Typical of these novel offerings is that they would not be feasible (economically at least) without ML technology. In contrast to the *process automation* subtype, where ML alters internal business processes, these applications are customer facing and change the offering itself (we illustrate the customer contact with a separate box in the right part of Fig. 5). Often, customers can tailor such products and services to their needs. An example is a content provider we interviewed that developed a service based on deep neural networks to automatically write penny novels. They offer this paid service to large publishing houses in order to generate content in an extremely cheap and fast way. At the time of our interview, the service was "currently able to influence the number of protagonists and … how creative this network should be … too much freedom usually ends up in some doomsday dystopia." (P11: Automatic writing). Another example, focusing on offering customer service for existing products, is a chatbot deployed at an energy retailer to quickly answer simple questions from customers, so that they do not spend time in the queue at the call center.

We summarize the overall characteristics of the three identified value creation mechanisms in Table 1 and differentiate them according to attributes that we described before.

Shifting ML value creation mechanisms

While analyzing the ML value creation mechanisms of all projects in our sample, we made two observations. First, we identified conditions that need to be fulfilled for successfully leveraging the identified ML value creation mechanisms and, in turn, achieving the aspired value targets. Second, we found that some ML applications changed their value creation mechanism over time and switched from one type to another. For example, there are over-ambitious ML automation projects which fail in the pilot project stage and, consequently, are reconfigured to task augmentation projects. Some data-intensive research projects, on the other hand, can evolve into ML systems that augment human tasks or fully automate processes. The following two vignettes illustrate the necessary conditions for the value creation types and illustrate the fact that some ML applications reconfigure over time. To unpack this phenomenon of reconfiguration, we first describe the identified conditions for each value creation type below and then explain the observed trajectories of reconfiguring projects.

Conditions for value creation mechanisms

We identified a set of necessary but not sufficient conditions that need to be fulfilled in order to successfully leverage the identified ML value creation mechanisms. These conditions can be internal (e.g., necessary assets or capabilities) or external to the company (e.g., necessary environmental factors). The conditions apply to the value creation mechanisms and the respective subtypes. We illustrate all the identified conditions as part of the process model in Fig. 6 and further explain them below. Conditions are inherited from mechanism to mechanism from left to right (i.e., the knowledge creation mechanism has two necessary conditions, the task

Vignette 1: Churn management in energy retailing (project 1)

An analytics vendor developed an ML-based process automation application for energy retailers to identify customers that are likely to cancel their contract (i.e., to churn). Based on the system's predictions, customers with high churn probability would be automatically approached with targeted advertising mail (*value creation through partly automating customer communication*). The churn predictions worked successfully in the lab using historical training and test data, but it turned out that the system had no effect on actual customer churn rates in the first field tests. In addition, the utility company had technical problems feeding the predictions back into their CRM system, which should send out advertising mails to customers. As a reaction to these difficulties, the project team started to investigate the drivers of customer churn to find out reasons for the good performance in the lab and the bad performance in the field trial (*value creation through knowledge creation about customers*). Once such drivers were identified, the vendor built a pilot and field tested in order to investigate how customers would react to targeted advertising in a churn context. After several rounds of development and testing of the new predictive ML model, both the predictive accuracy of the model and the estimated business impact of its implementation increased steadily. Eventually, the company integrated the churn scores into their CRM system via a newly-built interface (*value creation through task augmentation for account managers with high discretion to act on these insights*). After that, the application was extended to include the scores in the company's call center system. If the churn score of a customer exceeded a certain predefined threshold, the application prescribed specific questions for sales professionals to ask. Due to the fast response time in the call center, the agent has little chance to ask questions other than the suggested ones (*value creation through low-discretion task augmentation*).

Vignette 2: Pandemic disrupts marketing automation at a jewelry retailer (project 56)

A global jewelry retailer had already successfully automated its online advertisement process (*value creation through process automation*). However, during the Covid-19 pandemic, it found itself in new uncharted waters. The predictions of their ad placement algorithms were suddenly no longer as accurate as they used to be, leading to unsatisfactory, if not disastrous, advertising performance. After the first week of the pandemic, the company suspended their automatic advertising, and all marketing-related decisions were taken based on human judgment. Meanwhile, the company started a data-intensive research project (*value creation through knowledge creation about customers*) by collecting sales data about countries which were hit early by the pandemic (i.e., China, Italy). Based on these data, the company created interactive dashboards that would allow decision makers to quickly gain an understanding of the changing customer needs and behaviors:

> *"We have taken all our online and offline sales traffic and created a timeline and looked at 'during what events did sales start to change?'. Also, we have looked at all our media efforts: 'When did they leave?'. Then we created a picture based on it, to find the right model." (P56: Online advertisement process)*

Based on these data and insights, the company then started to train new predictive models tailored to the pandemic situation. In the third week of the pandemic, the company created a new decision-making team—they called it the SWAT team—acting across the owned and paid media channels of the global organization, using the output of the new predictive models as information for their decision-making. Hence, while ML was applied to create knowledge about customer needs (*knowledge creation*) in the beginning, it transformed to being used for routine decision-making (*value creation through high-discretion task augmentation*) over time. The initiative was still ongoing, but the midterm goal was to return to the old mode of ML-based process automation (*value creation through process automation*).

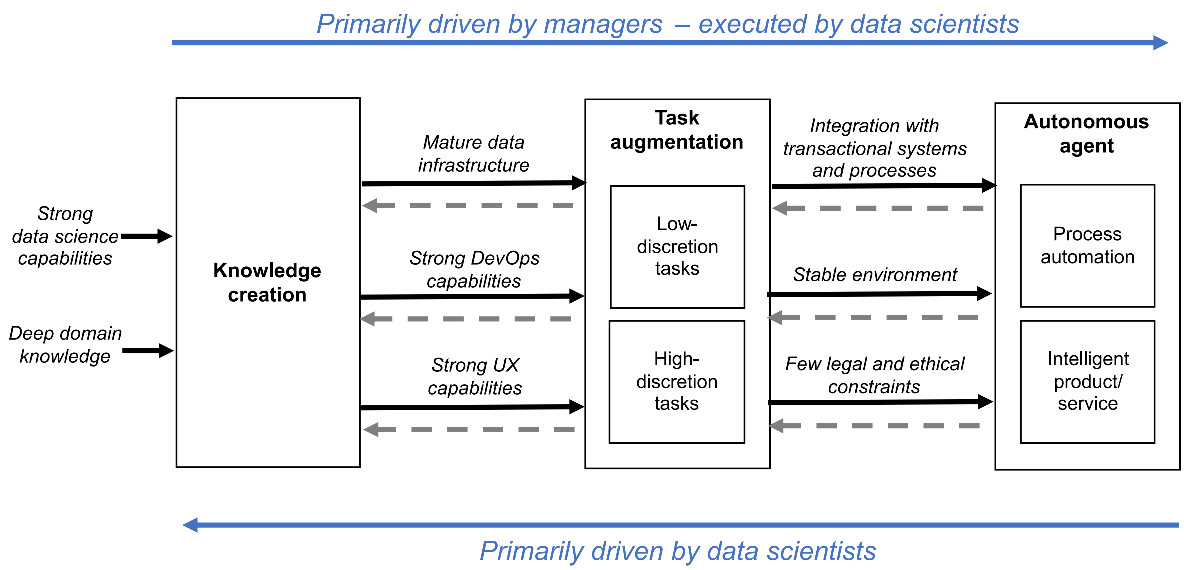

Fig. 6. ML value creation mechanisms and their necessary but not sufficient conditions: A process model of ML value creation in organizations.

augmentation mechanism has five necessary conditions, the autonomous agent mechanism has eight necessary conditions).

Two basic conditions are necessary to realize value from any of the three ML value creation types: *strong data science capabilities* and *deep domain knowledge*. Strong data science capabilities are, on the one hand, necessary for collecting and transforming the necessary data for ML applications and to allow for rigorous model development and evaluation. On the other hand, they are necessary to be able to communicate the often-complex outcomes of ML models to a broader business audience. Technical capabilities alone, however, are not sufficient to succeed with ML projects. *Deep domain knowledge* is equally important, as it enables people to understand the data generating process—the true (underlying) phenomenon that is creating the data—that they are trying to model. Although modern ML algorithms allow for a largely data-driven approach to modeling, deep domain knowledge is necessary to ensure a dataset that represents the phenomenon and does not produce biased results, and to detect causal mechanisms in observational data (when that is desired). It can both be brought in via data scientists' own domain knowledge or via domain experts from the business, which data scientists can consult. An interviewee at a global jewelry retailer emphasized:

"What is very challenging is to understand the data itself. Because my background is not really from retail, it's not really from marketing. So, I have to know at least 'what does this data mean?' Is it reasonable to have this kind of output, or what kind of input can I use?" (P45: Customer target groups for email campaign)

The two conditions, thus, form the building blocks to successfully leverage the *ML value creation* mechanisms. They allow an explorative and risk-averse approach to ML—centered around the question "What can ML do for us?", with *strong data science capabilities* answering the *"what can ML do"* part of the question and *domain knowledge* answering the *"for us"* part of the question.

Beyond these two basic conditions, we identified three necessary conditions to move from the knowledge creation mechanism to task augmentation mechanism: *mature data infrastructure*, *UX capabilities*, and *strong DevOps capabilities.*

We found that a *mature data infrastructure* is necessary to assure mid- and long-term success of task augmentation. Without a mature data infrastructure and the high-quality data it provides, even the most advanced ML technology cannot be fully utilized.

While a strong data foundation is a key enabler of ML, our informants reported that a carefully designed *user experience (UX)* - the way how a user interacts with and experiences a system—may be equally important. Especially for task augmentation applications, in which there is always a human in the loop, a positive user experience can avoid phenomena like algorithm aversion. One enabler for achieving a positive experience is to avoid the sole use of incomprehensible black box algorithms, either by using transparent models (e.g., linear or logistic regression, decision trees, and rule-based systems) which are inherently interpretable for users or by adding post-hoc explanation capabilities to highly complex model types like those based on neural networks. The following statement of an informant from a large bank exemplifies the need for interpretable ML algorithms in task augmentation systems:

"In most cases [users] ask like, 'Oh, but how does the algorithm work?' or 'Why did the algorithm give this low score or this high score?' … That is one of our challenges, because as per se, most of the ML models are black boxes. You do not know exactly what happens there." (P42: Fraud detection)

Finally, we found that for sustaining value realization of task augmentation systems, it is necessary to continuously monitor and improve data pipelines, models, interfaces, and actuators. Therefore, *strong development and operations (DevOps) capabilities* are necessary to assure the quality of ML-based systems. Such capabilities allow, for instance, raising warnings and adjusting systems whenever significant performance drops are observed.

"You don't put something into production and then just [run it]. It's very much about continuous monitoring and figuring out if there's a drift or changes [in the data]. … Traditional software keeps functioning the same way over time. Whereas ML models might degrade, or other stuff happens to [it when] the data changes. I think there's more complexity than the underlying system [alone]." (P32: Document matching natural language processing).

For successfully implementing autonomous agents, we identified three necessary conditions: *integration with transactional systems and processes*, *stable environment*, and *few ethical and legal constraints*.

We observed that many ML projects struggle with implementing automation systems, because they cannot easily achieve a seamless *integration with transactional systems and processes*. While it is usually possible to read data from transactional systems in a more or less timely manner, it can be difficult to write new data back into them. Even if the required legacy programming skills (e.g., Cobol, ABAP) were in place, it was hard for some projects to integrate ML systems with old transactional systems because they lacked interfaces. Another reason that we found were governance structures that do not allow data science teams to make required changes to transactional systems.

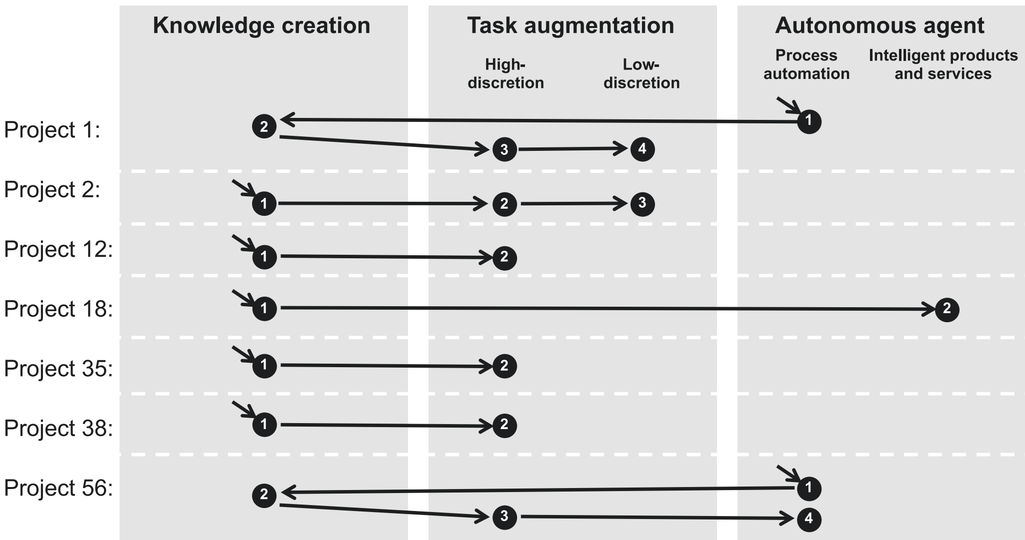

Fig. 7. Reconfigurations observed in our data.

It is essential that autonomous systems are deployed in a sufficiently *stable environment*. One of the main issues that we observed was that ML models were built under the assumption that the data generating process is stationary. However, changes to transactional systems, business processes, or the organizational environment can change the underlying data generating process. For example, frequent price changes in business-to-consumer settings are known to change consumers' buying patterns and, hence, will have negative consequences for the predictive accuracy of existing demand forecasting models. Such performance losses due to unstable data generating processes can draw a whole project into question, as one interviewee reported that their system after months in production showed *"a drift in the performance. And then [the stakeholder] didn't trust us as much as after that."* (P32: Document matching natural language processing).

Lastly, we observed that the success of autonomous agents can be dependent on the presence of *ethical and legal constraints*. While knowledge creation and augmentation systems always operate under human supervision (humans make final decisions and/or take actions), autonomous agents do not have any humans in the loop when making procedural decisions. Hence, it is essential to design and monitor these systems carefully to ensure that they act within the ethical and legal boundaries. The CTO of an analytics vendor gave an example of a situation in which they did not want to automate a process fully due to legal and ethical concerns:

> *"A client said recently: 'It's totally cool if you can automate this, but we will never do it, we always want to have a manual step in it… because then it's not profiling … because of data protection, compliance … otherwise every customer has to be informed and [has to] agree."* (P01: Churn prediction).

Reconfiguration trajectories

We noticed that for some projects, the value creation mechanisms changed over time as conditions changed or opportunities to advance to a more "mature" ML value mechanism emerged. We found seven ML applications in our sample in which such reconfigurations took place, and illustrate their trajectories schematically in Fig. 7. These trajectories suggest that a mismatch between a value creation mechanism and its necessary conditions is the main reason for value not being realized.

The dominant trajectory of ML applications in our data is from left to right, i.e., from knowledge creation to augmentation, then, to autonomous agents. Our interviewees mentioned several reasons. First, it seems that managers generally associate ML applications with automation. Our interviewees repeatedly reported that managers envisioned automated processes and had high expectations with regard to productivity gains. These inflated management expectations might support the tendency of ML projects to evolve towards automation as more conditions are fulfilled. Many interviewees reported that they need to educate business people on what problems can be solved with ML. One respondent explained:

> *"Automation is actually one of the challenges [where we have] to manage expectations, because people think much of AI—Fantastic! But it is not really like that.… Models come with errors, you cannot do everything, and you must explain the limitations." (P09: Automatic processing of health care policies).*

A reason why organizations did not start with automation projects right away, but rather tended to evolve their ML applications from "left to right" was risk management. Our interviewees referred to this evolution as a cautious approach to ML—which first implements prototype applications, then tests them in the lab, and finally deploys them in the field.

Starting with knowledge creation projects also allowed organizations to explore what ML can do for them, while providing relatively quick results. As the ML models became more stable (e.g., training data sets become more comprehensive), they could be further embedded in business processes and produce useful predictions for knowledge workers. If additional conditions were met and reliable results had been produced, the ML application became more autonomous and the process automated.

We also observed trajectories from right to left, i.e., automation projects that shifted to another value creation mechanism because certain conditions were not met anymore (see Vignette 2), or were never met from the start (see Vignette 1). In vignette 1, for example, the utility company could not feed predictions from the model into their transactional systems (condition: *integration with transactional systems and processes*). In vignette 2, the phenomenon under investigation (i.e., consumer behavior on the internet) was not stable anymore due to the Covid-19 pandemic and could not be modeled through ML (condition: *stable environment*). The project also changed scope by shifting to a different value creation mechanism and continued as a knowledge creation project before eventually evolving to a task augmentation system. The company could quickly release a "Corona dashboard," given that they met all conditions to shift to the task augmentation value creation mechanism. Another situation we observed multiple times, which led to right-to-left reconfigurations was inflated management expectations. Managers often pushed for full automation of processes, even when the necessary conditions were not present. This led to scope changes during the project lifecycle or sometimes after the ML application had been poorly implemented and no value could have been realized. One interviewee, for instance, was working on a new automated production planning system to optimize logistics at a large pharmaceutical company. Eventually, the system could not go live as its ML components lacked an interface to the existing planning systems, an issue that the technical team was well aware of. Management, however, seemed to expect a working fully automated ML solution, nonetheless (P29: Pharmaceutical company).

To enable reconfigurations, in general, a failure culture that allows organizations to put working prototypes into production, try them out, and learn from failures, seems necessary. An interview partner from a startup stated:

> *"You should not let yourself get demotivated by failures. It is not unusual to spend a month and a half gathering a dataset, then two weeks preparing the data, evaluating and analyzing it, and in the end, nothing comes out of it." (P10: Publisher consulting)*

In this section, we synthesized the empirical findings of our study into a process model of ML value creation (presented in Fig. 6). In the next section, we discuss its theoretical and practical implications.

Discussion

Inspired by recent studies indicating that AI value creation remains an ambition rather than a reality for many organizations (Brynjolfsson et al., 2017; Davenport & Ronanki, 2018; Fountaine et al., 2019; Ransbotham et al., 2017; Tarafdar et al., 2019), we investigated how organizations try to achieve their value targets with ML applications. We synthesized the empirical findings of our study into a process model of ML value creation (presented in Fig. 6), which we further discuss below.

A process model of ML value creation

Our process model highlights the complex and dynamic nature of the ML value creation and includes three main interrelated elements: ML value creation mechanisms, necessary but not sufficient conditions, and the shifting practice.

First, there are *three different ML value creation mechanisms and five subtypes* through which organizations can create value by pursuing specific value targets. Common to the three mechanisms of ML value creation is that they represent distinct ways in which ML applications contribute—through new knowledge, predictions, prescriptions, actions, or new value offerings—to the pursuit of value targets set by an organization. Therefore, our findings show that ML value creation mechanisms represent crucial elements in the ML value creation process (Grover et al., 2018; Hedström & Ylikoski, 2010). Each mechanism is executed by a different human-ML configuration, hence, it represents a different mode of delegation between humans and AI (Baird & Maruping, 2021). Our results thereby underpin the discourse on how to leverage the broader set of AI technologies to increase task-technology-fit with an empirically grounded set of ML technology uses (Makasi et al., 2021; Vimalkumar et al., 2021).

While the types and subtypes are not new per se, they do provide evidence that organizations employ them sequentially on a project level but simultaneously on a portfolio level to pursue different value targets from ML applications. Scholars have largely discussed the use of AI for achieving value targets through augmentation and/or automation mechanisms (Grønsund & Aanestad, 2020; Raisch & Krakowski, 2020). The ML value creation mechanism of knowledge creation has so far remained primarily detached from the augmentation and automation mechanisms (e.g., Berente et al., 2019; Tremblay et al., 2021). Yet, this new form of knowledge creation through ML-based models represents a new form of goal-setting for the use of ML in companies.

Second, for each mechanism, we found *a set of necessary, but not sufficient, conditions* that need to be fulfilled in order to successfully leverage the ML value creation mechanisms. The conditions indicate necessary capabilities and environmental factors in which organizations can leverage the different ML value creation mechanisms. The presence of all necessary conditions does not guarantee that a mechanism will produce the desired outcome (i.e., achieve the respective value target). But the absence of any necessary condition explains that organizations cannot successfully leverage the ML value creation mechanism. While previous studies recognize and mention many resources and capabilities necessary for successful implementation of ML applications (e.g., Akkiraju et al., 2020; Amershi et al., 2019; Fountaine et al., 2019; Mikalef & Gupta, 2021; Tarafdar et al., 2019), these resources and capabilities together with environmental factors have not yet been linked to specific ML value creation mechanisms. Without this integrated view, previous studies attribute the high failure rate to organizational implementation and restructuring time lags (Brynjolfsson et al., 2017). Hence, our process model provides an alternative explanation for high failure rate of ML projects and their poor business impact, as we demonstrate that the mismatch between the necessary conditions and the targeted ML value creation mechanism does not allow organizations to successfully leverage the ML value creation mechanism. Furthermore, our process model shows that necessary conditions are inherited from left to right, i.e., augmentation inherits conditions from knowledge creation and the autonomous agent mechanism inherits from task augmentation. This means that a growing number of conditions need to be met to leverage a tighter integration of ML into business processes (Fountaine et al., 2019). This is in line with computer science studies (Akkiraju et al., 2020; Garcia et al., 2018), which have also observed a correlation between automation and high maturity of ML applications.

Third, we discovered that, in dynamic environments, where capabilities and environmental factors change, shifting between ML value creation mechanisms is necessary to achieve and sustain value. The identified reconfiguration trajectories underline that strategic decisions about the ML value creation mechanisms are not static. Organizations have to constantly orchestrate their resources and capabilities based on organizational and environmental conditions in order to sustain value creation from ML applications (Markus, 2017). Thus, organizations need to configure and reconfigure their ML applications continuously to match changing conditions, which reflects the ML value creation orchestration and the dynamic capability of managing ML applications (Božič & Dimovski, 2019; Daniel et al., 2014; Pavlou & El Sawy, 2006; Pavlou & El Sawy, 2011; Zhang et al., 2021). As ML systems are different from other IT applications (Amershi et al., 2019), organizations need to develop new dynamic capabilities to sense changes in the environment, assess their impact on the ML effectiveness, and accordingly make necessary changes. It is especially crucial to monitor data generating processes, because the data generated today will become tomorrow's training data and, thereby, alter future ML models, which, in turn, will influence future predictions, prescriptions, or even decisions.

Having identified ML project reconfigurations, our data suggests that the left to right reconfiguration trajectory (i.e., moving towards autonomous agents) is driven by managers as the "desired evolution" driven by the economic logic to automate processes (Zuboff, 1985). This indicates a tendency of business managers to have positive evaluations towards delegation to ML models. In these situations, data scientists as operational managers seem to be the ones that understand the intricacies of delegation by making explicit both the capabilities of the ML models and the conditions that need to be in place for leveraging the ML value creation mechanism and actively pursuing the value target. This trajectory shows deliberate, planned steps of managerial actions. As data infrastructures, data science skills, DevOps and UX skills mature over time, or legal requirements change, new opportunities for resource orchestration emerge. These new opportunities are exploited by deliberately shifting the ML value creation mechanism and reconfiguring the human-ML configuration: i.e., delegating more and more to ML systems.

The opposite trajectory from right to left (e.g. automation projects that shifted to another value creation mechanism because certain conditions were not met anymore) also indicates resource orchestration. Contrary to the left-to-right trajectory, the resource orchestration is primarily driven by actions of data scientists in collaboration with domain experts. Data scientists—in this case acting as middle-level managers—seem to have the most knowledge about the limitations of ML systems. While ML systems have superhuman capabilities in terms of speed and scale (Lyytinen et al., 2020), they still remain limited as they have been designed to optimize an objective function. In other words, today's ML cannot set or modify their own goals (Aleksander, 2017). When changes in the environment occur, the competences of ML systems might be irrelevant, meaning that they might be fulfilling the wrong goals for the current situation. Hence, changes in conditions (organizational or environmental) signal that the ML value creation mechanism cannot be leveraged anymore. Therefore, data scientists engage in resource orchestration by sensing and identifying the changing conditions and changing the project scope to the adequate ML value creation mechanism.

These findings are in line with research on resource orchestration that points to the fact that different managerial levels are involved in the firm's resource orchestration efforts (Sirmon et al., 2011). For ML applications, top-level managers drive ML projects towards more automation while data scientists are more aware of the actual conditions and can suggest alternative trajectories for projects.

From a computer science perspective, reconfiguration is key to realign ML with changes in humans' problem understanding and ensure a high level of ML performance (e.g., Amershi et al., 2019; Sculley et al., 2015). From an organizational learning perspective, not only do reconfigurations have a positive effect on organizational learning, but reconfiguration intensities also play a significant role in establishing when "ML contributions to organizational learning become valuable enough to produce actual gains in the organization's knowledge" (Sturm et al., 2021). Our findings answer the so-far open question about when and how organizations should reconfigure their human-ML configurations from a resource orchestration perspective. We provide an explanation of why and when reconfigurations of human-ML arrangements happen and what trajectories these reconfigurations follow.

Theoretical contributions

Our process model contributes to the current literature on designing and implementing strategies in the context of ML systems in three ways. First, as mentioned in the background section, most studies on ML or AI value creation in organizations are either conceptual (e.g., Coombs et al., 2020; Davenport & Ronanki, 2018; Raisch & Krakowski, 2020) or pursue a variance perspective (Jöhnk et al., 2021; Mikalef & Gupta, 2021; Pumplun et al., 2019). This suggests lists of AI readiness factors (e.g., AI resources and capabilities that organizations need) without, however, necessarily taking into account that these capabilities or environmental factors might change over time. Our study contributes to this discourse by linking combinations of capabilities to ML value creation mechanisms and showing that a change in these combinations (deliberate or not) triggers a change in the value creation mechanism that can be leveraged. We know that strategic actions that effectively bundle and leverage existing resources have performance-enhancing effects (Morrow Jr. et al., 2007). Our empirically grounded process model not only contributes by providing more nuance into the pursuit of ML value creation through a set of ML value creation mechanisms but also explains *how* organizations engage in orchestration by *shifting between ML value creation mechanisms* as their capabilities evolve and business conditions change.

Second, by taking a process perspective on resource orchestration, we focus on the actors and the actions they take to leverage the adequate ML value creation mechanisms in dynamic environments. In this regard, our study contributes by highlighting the emerging role of data scientists as orchestrators. Recent studies have also pointed to the increased role of data scientists in pursuing and creating value through ML applications (Grønsund & Aanestad, 2020; Joshi et al., 2021; Pachidi et al., 2021; Vaast & Pinsonneault, 2021; van den Broek et al., 2021). Adding to this growing body of work, our study illustrates how data scientists act as middle-level managers in creating uniquely complementary resource bundles by integrating organizational capabilities, considering environmental factors, and shifting between ML value creation mechanisms in their pursuit of value creation through ML technologies. This shifting practice enables organizations to leverage AI-driven "novel human–machine capabilities" that complement traditional competitive capabilities in organizations with those of ML-based systems (Krakowski et al., 2022). Our process model further extends the findings of Krakowski et al. (2022) by contributing an integrated evolutionary view of how these novel human–machine capabilities can be built and leveraged in organizational settings.

Third, on a broader scope, our process model also contributes to the IS and data-intensive value creation studies. In particular, we further unpack previous value creation process models (Grover et al., 2018; Soh & Markus, 1995; Zeng & Glaister, 2018) and show concrete relationships between capabilities and value creation mechanisms. This allows a deeper understanding of the transformation that takes place from the capability building process into the capability realization process (Grover et al., 2018). At the same time, these previous process models focus on just identifying value creation mechanisms for IS and do not account for relationships between the different mechanisms. Instead, the focus of our process model is the shifting between the value creation mechanisms. This demonstrates interaction between different value creation mechanisms, which lead to concrete orchestration paths through which organizations pursue value creation. We believe that this novel perspective opens up a new direction for future research in the area of IS value creation process, considering links and interdependencies among different data-intensive value creation mechanisms.

Practical implications

Our research has four main implications for practitioners. First, the identified ML value creation mechanisms and conditions are effective management tools for the strategic positioning of ML initiatives. Both top-level managers (e.g., executives) and middle level managers (e.g., business managers or data scientists) can use the mechanisms and the conditions as guidance for formulating value targets for ML projects. In particular, our Table 1 helps in selecting the most effective type of ML use based on the intended value contribution (organizational knowing → Mechanism 1, more effective decision-making → Mechanisms 2a and 2b, increased productivity / novel value offerings → Mechanisms 3a and 3b). Likewise, the architectures illustrated in Fig. 5 can act as blueprints for designing ML systems and their interactions with users and the environment (e.g., whether to implement an indirect or closed feedback loop, whether to automate decisions through ML or let the human decision makers have the final word). This clarity helps to avoid situations where applications of ML are evaluated based on performance measures that do not apply to their specific types (e.g., the use of predictive accuracy for an interpretable model or the insistence on explainability without a need for it) or there are inconsistencies in the division of labor between ML and human. Second, we underlined that ML applications can be based on diverse value creation mechanisms, focusing not only on automating or augmenting, but also on creating new knowledge. Firms should consider the complete bandwidth of value creation mechanisms to achieve the whole variety of value targets, for example by using ML in innovation or research and development processes. Third, knowing the identified conditions and the fact that reconfigurations are not only possible but rather inevitable helps firms sustain value creation over time. Firms should also update their ML strategy based on this knowledge and allow for incremental improvements (e.g., start with experimental pilot projects in labs and integrate them into productive processes when technical infrastructures and processes are mature enough), and proactively shift the value creation mechanism when conditions are no longer met. To enable this shifting, managers should establish an iterative reflective process to allow for unforeseen reconfiguration of projects so that they continue to create value, even if the value target changes over time or different environmental factors were anticipated. Fourth, the identified conditions inform executives, but also data scientists and ML project managers, about possible problems and mitigation approaches (e.g., what alternative paths for ML projects exist to sustain value creation when conditions are not met anymore or when new opportunities arise). They also provide decision support for AI strategists and managers to (re-)adjust the ML value creation mechanisms adopted by projects, as well as the development steps that need to be undertaken for sustaining ML value by shifting value targets as conditions change. This is particularly important, as a change in conditions means that the pursuit of a value target is at risk.

Conclusion

Over the last years, IS and management scholars have repeatedly called for empirical research on the strategies that organizations employ to pursue their organizational goals and create business value from AI (e.g., Coombs et al., 2020; Galliers et al., 2017; Markus, 2017; Rai et al., 2019; Raisch & Krakowski, 2020; von Krogh, 2018). With this study, we contribute to research on the management of AI and specifically ML-based AI applications by proposing an empirically-grounded process model of ML value creation mechanisms, conditions, and reconfigurations. This process model explains the orchestration efforts of data scientists in leveraging diverse value creation mechanisms in their effort to pursue value targets. Our findings assist in understanding why many organizations struggle with managing ML applications and leveraging them to meet their value targets. At the same time, the process model provides practical guidance for managers to navigate the largely uncharted waters of the ML value creation process.

In this study, we go as far as identifying ML value creation mechanisms and associated necessary conditions. Due to the explorative nature of this research, the identified ML value creation mechanisms are possibly not exhaustive. Furthermore, we cannot quantify the exact value that ML creates in these organizations. Explicitly, we do not capture the functional and symbolic impact these ML applications have on organizational performance (Grover et al., 2018). Future studies, similar to those on the impact of big data analytics on firm performance (Müller et al., 2018; Tambe, 2014; Wu et al., 2019), should add an economic point of view on the impact of ML applications in organizations. It would be also interesting to investigate if there is a correlation between the type, size, and digital (ML) maturity of a company and the types of ML value creation mechanisms that they exploit.

Reflecting on our methodology, and as ML applications are being increasingly diffused in organizations, we acknowledge that interviewing more stakeholders involved in ML application management and use (e.g., users, decision makers, strategists, business domain experts), as well as gathering value-related artifacts (e.g., business cases, cost benefit analysis, benefit realization measures and reports) would provide a more holistic view while also unpacking the micropolitics of the ML value creation process.

Furthermore, our study takes the perspective of data scientists which have emerged into operational as well as middle level managers and shows their orchestration efforts in pursuing organizational goals. While this is an important contribution of our study, since most studies on the management of AI so far focus on top-level managers (Fountaine et al., 2019), it would be interesting to have studies that investigate the synchronization efforts that span different managerial levels in organizations.

In our study, we also did not focus on the unintended consequences of ML applications (Newell & Marabelli, 2015)—an aspect that might severely impact value creation while at the same time allow for broader conceptions of value (like societal value) to be taken into account. Longitudinal case studies might provide richer insights into the unintended consequences of ML applications and their impact on value creation. While our findings are a first step towards understanding the intricacies of ML value creation processes in organizations, future studies could build on the limitations and provide additional contributions in this research area.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jsis.2022.101734.

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