Lessons Learned from a Case Study: a Diamond Model for Implementing and Scaling Process Mining

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Abstract. Companies should ensure that they constantly improve their business processes. Digital technologies stand out in doing so. Latest process mining technologies are key enablers for process improvement as they endorse the identification, (re-)design, implementation, and scaling of leanest processes. However, since there is no operating model covering this endeavor, many organizations are struggling especially how to implement and scale process mining initiatives. Accordingly, the objective of this article is to develop an operating model for process mining. We refer to it as the diamond model and group it into (1) drivers of the model, and (2) enablers for process mining. We derive seven lessons learned on how to best leverage process mining in companies. Underpinned by the results from our literature review, these lessons learned should help other companies willing to implement and scale process mining for its value creation. For research purposes, we present future research opportunities.

Keywords: Process Mining, Operating Model, Business Value, Case Study, Design Science Research in Information Systems.

1 Introduction

Companies should ensure that they constantly improve their processes. Today, digital technologies such as artificial intelligence (AI), blockchain, the Internet of Things, and process mining support them in doing so [1]. Identifying, (re-)designing, implementing, and scaling leanest processes by extracting knowledge from event logs that are available in a company's information systems (IS) [2], *process mining* is a key enabler for process improvements [3].

Accordingly, process mining has become a top 3 priority in a company's project list [4]. The aim is to automatically discover, monitor, and improve real processes by extracting knowledge from event logs readily available in today's IS [2]. Extracted data is the foundation of process models, so existing process flows can be visualized, analyzed, and redesigned in subsequent steps – ultimately to improve business processes.

However, many organizations are still struggling especially when implementing and scaling process mining initiatives since there is no operating model covering this endeavor. *Operating models* should encompass governance bodies, roles and responsibilities, as well as process landscape and knowledge management. Furthermore, they should help in defining, structuring, and monitoring different aspects required to run process mining initiatives. Last but not least, operating models should advise process owners on how to improve their processes best [5].

Examining current literature, Langmann and Turi [6] elaborated on how to leverage digital technologies for process improvement. Applying robotic process automation (RPA) should help to streamline workflows, making organizations more profitable and responsive. Following Bozorgi et al. [7], the elimination of non-value-adding processes in an organization should be key for companies. Van Eck et al. [8] provided a framework for sequential steps of process mining. Kipping et al. [9] elaborated on role-specific requirements, and faced challenges such as missing commitment and overcoming internal resistance, but did not give answers on how to solve them. Furthermore, they focused on the implementation of digital technologies, but not on the subsequent *business value creation*. Grisold et al. [10] addressed this shortcoming by examining organizational and managerial issues. However, they stated that process owners still face challenges in quantifying it as an operating model is missing which includes measuring business value.

Accordingly, the objective of this article is to develop an *operating model for process mining* which we refer to as the diamond model. Starting with a literature review, we decided to conduct a Design Science Research (DSR) in IS study [11, 12]. We cooperated with a science and technology company as our case company, which was redesigning its order-to-cash (O2C) process. The seven lessons learned from this study, we finally present, should help companies apply process mining for business value creation. For research purposes, we present avenues for future research. We pose two research questions (RQ):

- **RQ1**: What constitutes an operating model to implement and scale process mining for a company's business value creation?
- **RQ2:** Evaluating the presented operating model, how can our lessons learned be improved for ensuring validity and utility?

Following the publication scheme of Gregor and Hevner [13], the structure of this article is as follows: Having motivated this article in terms of missing operating models for implementing and scaling process mining (*Sect. 1, introduction*), we highlight several research gaps. We then contextualize our research questions (*Sect. 2, literature review*). Addressing these gaps, we conduct a DSR in IS study (*Sect. 3, method*). Emphasizing a staged process with "build" and "evaluate" research activities [14], we develop the proposed operating model (*Sect. 4, artifact description*, related to RQ 1). In order to test its validity and utility, we perform semi-structured expert interviews within and beyond the case company (*Sect. 5, evaluation*, related to RQ 2). Comparing our lessons learned with prior work, and examining how they relate back to the article's objective and research questions, we close with a summary, the limitations of our work, and suggest future research projects (*Sect. 6, discussion and conclusion*) [15].

2 Literature Review

Following Webster and Watson [16], as well as vom Brocke [17, 18], we identified relevant articles in a four-stage process. (1) We focused on leading IS journals as well as BPM journals, complemented by proceedings from major IS conferences (*outlet search*). To obtain a practitioner perspective, we considered journals such as MIS Quarterly Executive and Harvard Business Review. (2) Accessing these outlets, we used ScienceDirect, EBSCOhost, Springer Link, Emerald Insight, and AIS eLibrary (*database search*). (3) We then searched for articles through their titles, abstracts, and keywords (*keyword search*) – limiting the results to the last ten years.

Applying this strategy for our research, we combined process mining, operating model, and business value with the Boolean operator "and," which yielded zero hits (Row 1, Figure 1). We then immersed into each of the three pillars separately by substantiating (1) process mining with process discovery, conformance checking, and process enhancement (Column 1, Figure 1), as well as (2) operating model by means of governance bodies, collaboration model, and organizational framework (Column 2, Figure 1).

We detailed business value by process redesign, re-engineering, and standardization (Column 3, Figure 1). Searching for these keywords individually, we assessed the articles regarding their relevance for our research, starting with analyzing their titles, followed by their abstracts and keywords, as well as the content of the articles themselves. In doing so, we found ten relevant hits for the first pillar, four for the second one, and another thirteen for the third one. Furthermore, we found six practitioner publications.

Finally, we conducted a (4) *backward and forward search*. With references from all publications, we identified another fifteen publications and ended up with 48 publications in total. Figure 1 depicts our search string with the number of relevant publications.

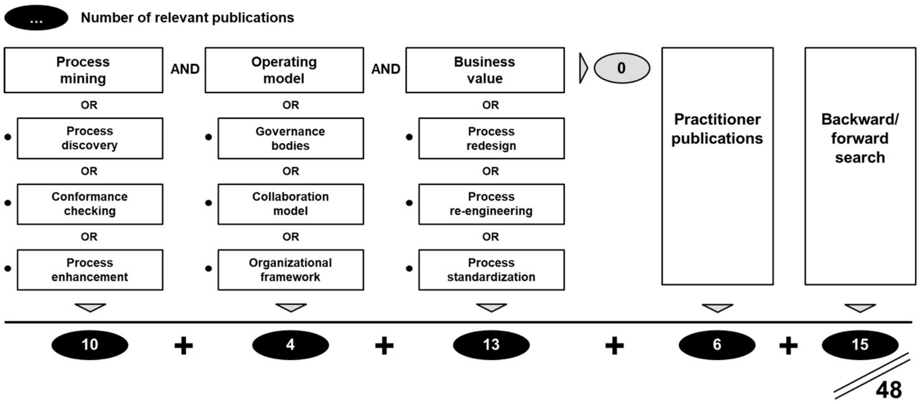

Fig. 1. Search Strategy.

For our **gap analysis**, we structured the relevant publications into three clusters: (1) We elaborated on recent developments in process mining. (2) We then examined components for operating models. (3) Finally, we discussed process mining implementations with a focus on their business value creation as follows:

(1) Implementing **process mining**, we examined studies, which focus rather on the implementation, but not on scaling lessons learned from pilot projects [8, 19]. In doing so, van Eck et al. [8] introduced the Process Mining Project Methodology (PM^2). Aguirre et al. [19] applied an engineering approach based on requirement analysis.

Both publications present *sequential methodologies*. While examining success factors for process mining, Mamudu et al. [20] demonstrated interdependencies based on 62 case reports, focusing on the prerequisites for successful process mining, e.g., “technical expertise,” “stakeholder support,” or “information availability”. In turn, Mans et al. [21] identified not only success factors, but also how to measure the success of process mining by considering model quality, process impact, and project efficiency.

However, we did not find any publication examining both, levers on how to implement process mining best and scaling the lessons learned across the company. Accordingly, we recommend setting up an *approach for implementing and also scaling process mining across the company*.

(2) Regarding the **components of operating models**, Hylving and Bygstad [22] elaborated on Enterprise Architecture Management (EAM) which triggered employee responses such as loyalty, voice, and exit. While voice is a reaction of resistance, maintaining loyalty for successful projects is reached through continuous communication, especially with skeptical employees and departments [23]. In 2021, vom Brocke et al. [24] proposed a *five-level framework for research* on process mining. Guided by Hevner and March [11], who described a technical, people, and organizational level for analysis, people were divided into individual and group levels. Ecosystems were added complementary. The resulting five levels of analysis are: *Ecosystem, organization, group, individual, and technology. Ecosystem* focuses on the effects of process mining on inter-organizational relations, e.g., value chains and networks. *Organization* assesses the effects of process mining on operations and value creation, e.g., organizational success. *Technology* covers the process mining tools, e.g., the design of the IS platform. While *individual* describes the process mining effects on people’s perceptions, behavior, and skills, *group* focuses on people’s interaction and the mode of work.

Furthermore, the *O2C process* is a good starting point for implementing process mining [25, 26]. By optimizing cash management, companies are better prepared for mitigating economic discontinuities, even shocks such as the onset of the COVID-19 global pandemic [27]. Focusing on value creation in the O2C process, The Hackett Group [28] proposed days sales outstanding (DSO) as the most important KPI. Coming to our second takeaway, we propose to instantiate an operating model for process mining adapting the *five-level framework* by vom Brocke et al. [24] and starting in the *O2C process* of our case company.

(3) Eggert and Dyong [29] applied process mining in a small IT enterprise. Performing a single case study, their main challenge was to present value creation. In doing so, their guidelines stated starting with a simple process and focusing on core functionalities of process mining. For **business value** creation, Rosemann and vom Brocke [30], suggest six core elements: Strategic alignment, governance, methods, information technology, people, and culture.

Focusing on *strategic alignment*, Grisold et al. [10] elaborated on process managers handling organizational and managerial issues when implementing process mining. The authors found evidence of distrust and perceived surveillance due to transparency after application. Accordingly, clear communication, demonstrating that process improvements support employees, is key. Kipping et al. [9] underlined the importance of this research, as they argue that an understanding of managerial and organizational implications through technology is just beginning. Their findings indicate that different roles are associated with different tasks, skills, and additional technology usage. This means that capabilities in IS projects must be thought of multidimensionally to create business value.

Governance orchestrates process mining and results in continuous process improvements [31]. A structured mining approach, as well as a clear framework with dedicated expert roles, such as product owner, data architect, or business expert, ensures smooth operations and clear responsibilities within a process mining project [20, 21].

Focusing on *methods and information technology*, there are traditionally two goals for implementation: (1) Analytics is dominated by the use of process mining, but pattern recognition using AI is also a well-established theme [32]. (2) Automation is often implemented with RPA, but AI [33] or BPM systems [34] following initial process mining insights are also applied.

Focusing on *people and culture*, Müller et al. [35] theorized the impact of organizational priorities on the success of business transformations. Business value creation should not only focus on processes and IS but also includes how employees work [36]. Kudaravalli et al. [37] examined coordination within software teams and came up that an agile approach is better than a centralized one. Following Ahmad and van Looy [38], social BPM for creating business value is an emerging topic [9, 10]. Accordingly, we derive a third takeaway to implement and scale our operating models for process mining. It should incorporate *collaboration principles* in order to leverage human expertise incl. interaction with IS, ultimately to foster collaboration for business value creation.

3 Method

Guided by the findings from our literature review (Sect. 2) and following Morana et al. [39], we decided to conduct a *DSR in IS study in a case company*. It is a supplier of pharmaceutical, laboratory, and electronic products, serving a high number of business clients. Due to manyfold mergers and acquisitions during the last decades, its IS landscape is heterogeneous. Furthermore, the case company faces a high number of incoming invoices, so the processes need to be automated. Consequently, the case company decided to rework its O2C process with the latest process mining technology, as it expects to gain significant free cash flow – ultimately business value from the improved processes.

Case studies are examinations of a contemporary phenomenon within its real-life context [40]. They bridge the gap between practice and academia when there is little research on this topic and practical insights are considered important [41, 42]. Compared to surveys, they provide more substantial in-depth information and enable researchers to study their artifacts in a natural setting [43]. Compared to multiple case studies [44], *single case studies* are more suitable when the research topic is complex, and thus, relevant starting points for research are not easy to obtain [15, 45].

Following Eisenhardt [46, 47], we commenced our project with *desk research*, focusing on the finance domain. We examined internal documents, assessed the main processes, and selected the O2C process intending to increase the companies' liquidity.

In parallel to our structured *literature review*, we looked at Celonis demos and handbooks. To document the as-is process status of the case company, i.e., existing process inefficiencies, we conducted *workshops* with participants from nine finance-related departments, such as group accounting. The workshops lasted an average duration of 47 minutes and included 37 participants in total. Further, the results were anonymously posted on an interactive whiteboard and transcribed after each session for documentation in a single source for further analysis. Finally, we deleted the mentions from each session from the whiteboard to avoid bias for future participants.

Following Mayring [48], we then performed a *qualitative content analysis*, which enables a systematic, rule-based procedure by applying a category system [49]. We assigned the identified process inefficiencies based on their meaning into categories, whenever it was meaningful. If the semantic label would not fit into any existing category, a new one was created. For instance, if "[lack of] transparency and documentation" would not yet fit, the category "C6: Transparency" was created. This procedure was performed for all protocolled process inefficiencies. These items were then again assigned to the five assessment levels (AL) from vom Brocke et al. [24]. Table 1 lists the final category system of our qualitative content analysis displaying the final selection of *categories of the operating model* (Column 2, Table 1).

Given the number of consistent mentions in the workshops, we counted the semantic labels in each identified category (*frequency analysis*) and ranked them (Table 2). By doing so, we identified two groups of categories, namely *(1) drivers of the model* and *(2) enablers for process mining* (Column 4, Table 2). Then, we designed the instantiation of our operating model (RQ 1, Sect. 1) and revised it with two experts from the project team, whenever we identified potential aspects for improvement.

Table 1. Category system of our qualitative content analysis.

Assessment levels	**Categories of the operating model**
AL1: Ecosystem	C1: Close monitoring, C2: Capabilities
AL2: Organization	C3: Strategic process focus, C4: Roles and responsibilities
AL3: Technology	C5: Strategic platform, C6: Transparency, C7: Data quality
AL4: Individual	C8: Knowledge, C9: Training
AL5: Group	C10: Collaboration, C11: Implementation method

Examining the impact of each category, we applied a *quantitative analysis*, which was based on a questionnaire and applied a five-point Likert scale. The questionnaire was completed by eighteen participants from the project team, who are process mining experts, experts from Finance or IT, and O2C operators. A selection of functional knowledge, as well as process mining experience, ensured the independence of answers from each participant, thus yielding heterogeneous results. We calculated the medians and means, which guided us in prioritizing the most beneficial levers (Table 4).

Evaluating artifacts is a major activity in DSR in IS [50]. We opted for four semi-structured expert interviews within and beyond the case company, which took an average of 50 minutes. As suggested by Rowley [51], we determined the number of participants with the level of saturation, meaning that we stopped considering further participants once we could no longer expect to gain additional useful insights. Guided by

Gregor and Hevner's [52] proposed evaluation criteria, we gathered feedback about the utility and validity of our operating model (RQ 2, Sect. 1). Following Peffers et al. [14], DSR is an iterative process, which means, that the artifact should be continuously evaluated and redesigned until saturation is reached, i.e., no further improvement can be expected.

As our purpose was to acquire the interviewee's knowledge as comprehensively as possible, we considered interviews [53]. In comparison to surveys, these extend deeper into the subject matter, which can be useful for a later quantitative evaluation. We applied *semi-structured expert interviews*, because they combine a comparable structure within a series of interviews, whilst still being flexible when interviewees want to share individual insights and thoughts that might otherwise remain hidden [54].

4 Artifact Description

Starting with the qualitative content analysis (Sect. 3), we assign semantic labels to the categories of the operating model and rank them according to the number of mentions (Sect. 4.1, Table 2). Then, we develop the recommended *design of the diamond model* for successful process mining in our case company (Sect. 4.2). To assess the importance of each category, we conducted a quantitative analysis resulting in key categories for further investigation (Sect. 4.3).

4.1 Content Analysis

Based on our workshop notes, we identified *269 semantic labels* of process inefficiencies and grouped them into eleven categories (Sect. 3, Table 1). They represent the umbrella terms best matching the meaning of semantic labels. Counting the numbers (Column 3, Table 2), we ranked them accordingly (Column 1, Table 2).

Table 2. Grouping of operating model categories.

Rank	Categories of the operating model	Ratio of mentions (N=269)	Group of categories
1	Strategic platform	44/269 (16.4%)	Drivers of the model
2	Collaboration	37/269 (13.8%)	
3	Strategic process focus	32/269 (11.9%)	
4	Roles and responsibilities	26/269 (9.7%)	
5	Knowledge	25/269 (9.3%)	
6	Training	25/269 (9.3%)	
7	Implementation method	24/269 (8.9%)	
8	Close monitoring	16/269 (5.9%)	Enablers for process mining
9	Transparency	16/269 (5.9%)	
10	Data quality	14/269 (5.2%)	
11	Capabilities	10/269 (3.7%)	

We made a *cutoff* between ranks seven and eight, as these items have the greatest difference in our analysis. Accordingly, we defined seven *drivers of the model*, followed by four *enablers for process mining* (Column 4, Table 2). Drivers were mentioned more often and perceived as more important than enablers, which were mentioned as boundary conditions for facilitating process mining.

4.2 Operating Model Design

Following the five-level framework by vom Brocke et al. [24] which spans the corners of the diamond design (Sect. 2), we recommend an operating model that contains two components:

(1) Drivers – enhancing performance: We analyzed eleven levers for successfully implementing and scaling process mining, and the top seven were classified as drivers of the model (Column 4, Table 2). These are *strategic platform, collaboration, strategic process focus, roles and responsibilities, knowledge, training,* and *implementation method* (Column 2, Table 2). They address the human-related assessment levels of *organization, individual,* and *group* – consistent with the findings from our literature review. The only exception is the *strategic platform* focusing on the *technology* level.

The drivers of the model directly enhance the performance of the operating model and can be represented mathematically by a linear function. This indicates that drivers enhance performance when properly applied but can also degrade it when this is not the case. Applied to our case company, if, for example, IS are not properly connected to the *strategic platform*, this will lead to poor performance of the operating model, because process mining can only be applied in the IS that are currently connected. Thus, leveraging event data is key for performance by identifying and connecting the right IS in advance. Ultimately resulting in the overarching objective of building and managing a digital twin, this will lead to valuable strategic insights.

(2) Enablers – securing performance: Enablers for process mining secure the performance of the operating model. Enabler categories are *close monitoring, transparency, data quality,* and *capabilities* (Column 2, Table 2). As enablers secure the performance, their absence would lead to issues regarding the general process mining activity. For example, bad *data quality* leads to a delay, as data cleansing then becomes necessary. Enablers for process mining can be approximated as a dummy function, while the conditions can be defined as follows: If one specific enabler hinders process mining activity, it will result in “0,” otherwise it will be “1” securing the performance.

4.3 Key Categories of the Operating Model

Evaluating the categories’ importance, we performed a questionnaire-based *quantitative analysis* of their impact on process mining with the project team (N=18). The project team included process mining experts, subject matter experts from Finance and IT, O2C operators, and consultants from the implementation partner. A careful selection of broad functional knowledge, as well as process mining experience, yielded heterogeneous results. To quantify the impact of each category regarding the process mining model, we applied a five-point Likert scale ranging from “strongly disagree (“1”) to "strongly agree ("5","). We then calculated the median and mean values of the categories to be evaluated. Since the median is not affected by outliers, compared to the mean, we chose it as a ranking criterion and *cut it off* between ranks five and six (items with the greatest difference in our analysis).

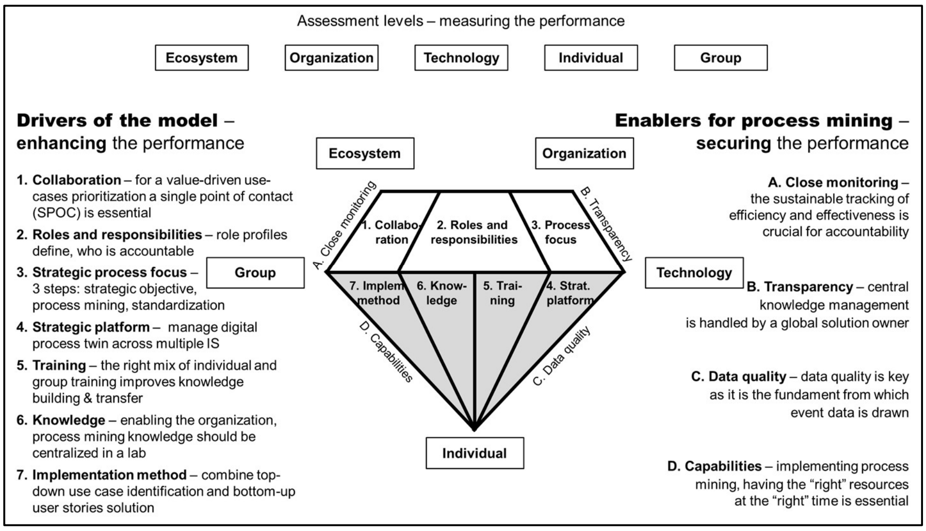

Fig. 2. Diamond model for process mining.

Table 3. Prioritization of categories.

Rank	Categories of the operating model	Median/Mean (N=18)	Prioritization
1	Capabilities	5.00/4.61	Key categories
2	Strategic platform	5.00/4.44	
3	Data quality	5.00/4.44	
4	Collaboration	5.00/4.39	
5	Knowledge	4.50/4.33	
6	Training	4.00/4.39	Complementing categories
7	Roles and responsibilities	4.00/4.17	
8	Close monitoring	4.00/4.17	
9	Transparency	4.00/4.00	
10	Strategic process focus	4.00/3.94	
11	Implementation method	4.00/3.94	

We then prioritized the categories by ranking them according to the impact of these levers (Column 1, Table 3). This finally yielded the five *key categories* of *capabilities, strategic platform, data quality, collaboration,* and *knowledge* – followed by six complementing categories (Column 4, Table 3). We then examined key categories in a deep dive as follows: We set the ranking from the questionnaire as priorities and enriched these categories with the *information given in the questionnaire* (free text-field question) as well with *insights and explanations* of the 269 semantic labels *from the workshop series* (Sect. 3) to finally derive our lessons learned.

Priority 1 "capabilities" – focusing on *budget restrictions* for the capabilities available at the right time and translating a scrum methodology into action, we recommend bundling different capabilities efficiently in so-called *dailies*. These are short alignment meetings of about half an hour on a daily basis over the complete project period. Sharing expertise in such a way, we experienced an efficient resource allocation, while fostering cross-functional exchange. Instead of single blocks full-time, we present the first lessons learned.

Lesson learned #1: Bundle capabilities in dailies. They last up to 30 minutes and synchronize developers & business experts whilst removing roadblocks in advance.

Priority 2 "strategic platform" – applying an IS prioritization regarding their input, harmonization, and process-to-technology map, the latter shows how end-to-end processes should look, and which technologies have to be applied. With the objective that every business-critical process should have a digital twin, *standard technologies* need to be established. We deduce the second lesson learned.

Lesson learned #2: The more different IS are connected, the more powerful is the process mining platform. For critical processes, design a digital twin.

Priority 3 "data quality" – since process mining technology uses event data, they are fundamental to gaining insights. The participants from the workshops stated that they typically focus threefold: Data cleansing is needed, when there are errors in a dataset. Data validation is about compliance following predefined regulations. Most important, *data standardization* covers the uniform definition of data. It can be applied by *master data governance* and *master data management* – both aim to establish clear ownership of data. Finally, all data incl. its corresponding attributes should be stored in one repository, that is the *data catalog*. We present the third lesson learned.

Lesson learned #3: Set up data standardization threefold by (1) data governance, (2) clear data ownership, and (3) a data catalog.

Priority 4 "collaboration" – concluding that collaboration is an important lever for instantiating and executing an operating model, employees had a strong preference for "establishing channels for quick action," while others noted that "more transparency in communication is key when finding the root causes of process inefficiencies" is needed. Combining these results, a single point of contact *(SPOC)* has to prioritize use cases, whilst shortening communication channels and driving transparency. This can be performed by a product or a business process owner. Fostering collaboration, we implemented a collaboration model, which involves decision makers in prioritizing use cases to elaborate on, and applied the scrum methodology bottom-up in such projects. Beyond traditional waterfall approaches and following Schwaber and Sutherland [6], we recommend an agile method as state-of-the-art in software implementation projects [7]. The advantage is flexibility in building and combining modular increments while maintaining project performance. We come up with a fourth lessons learned:

Lesson learned #4: Prioritize most value-driven use cases and set up a SPOC to continuously orchestrate collaboration.

Priority 5 “knowledge” – building knowledge about processes and IS centrally as well as gaining a sound business understanding are major aspects. Consequently, holistic processes and IS knowledge are important drivers of an operating model. *Centralized in a lab*, it has to combine a top-down use-case prioritization and a bottom-up user-story solution using agile methodologies. We deduce a fifth and final lesson learned.

Lesson learned #5: Gain a strong understanding of business processes within a centralized lab whilst combining a top-down use-case prioritization and a bottom-up user-story solution.

5 Evaluation

Referring to RQ 2 about our operating model’s validity and utility (Sect. 1), we conducted four semi-structured expert interviews averaging 50 minutes. Internally with the IT Process Owner Account-to-Report (A2R) and the Head of Continuous Business Improvement of the case company, and with the Director of Accounts Receivable (AR) of a healthcare provider and the Head of Global Accounting of a technology group. To avoid bias, the interviewees were not part of the expert group which constituted the model design. Regarding the operating model’s **validity**, we summarize as follows.

Discussing the allocation of capabilities, the Head of Global Accounting of a technology group explained that the project team comes together once or twice each week. However, they have no *dailies*. Furthermore, employees of the technology group use an alternative to meetings, that is MS Teams’ chat feature, to discuss smaller topics that come across in their daily work. The Director AR of a healthcare provider underlined the need to schedule meetings only on demand and not continuously if there are no topics to discuss. He recommended tailoring meetings flexibly in response to the current demand and – more important – including only necessary employees to elaborate on a specific topic. Both internal interviewees, the Head of Continuous Business Improvement and the IT Process Owner A2R, emphasized that operational day-to-day work should not be affected by project participation, and for ad-hoc issues, asynchronous communication channels should be considered. Accordingly, we update lessons learned #1 (Sect. 4.3).

Adjusted lesson learned #1: Bundle capabilities in dailies. They last up to 30 minutes and synchronize developers & business experts whilst removing roadblocks in advance. For ad-hoc issues, consider asynchronous communication channels.

We then asked if all business-critical processes should have a *digital twin*. The Director AR answered that this is desirable, but should follow a benefit/effort ratio. This means that digitalizing the most important processes in IS makes sense as long as the event data from these IS sufficiently explains activities and flows within the respective process. The Head of Global Accounting of the technology company emphasized that a digital twin increases transparency and supports data-driven decisions. We conclude that our lesson learned #2 is valid in terms of content, but needs to be reformulated as follows to further specify:

Adjusted lesson learned #2: The more different IS are connected, the more powerful is the process mining platform. For critical processes, design a digital twin if the benefits justify the effort based on a solid business case.

Regarding *data standardization*, the Head of Global Accounting states that a data catalog with a definition of important suppliers, buyers, and market data is important. The composition of all data is seen as an important challenge in the future. In turn, the Director AR of the healthcare provider has not seen a data catalog so far but strongly favors the idea of centralizing technical attributes in one document. The challenge of such a single source of truth is its maintenance, as an organization generates more and more data every day. These statements validated our *lessons learned #3*.

A *SPOC* should prioritize use cases for the case company and orchestrate collaboration. Both the Director of AR and the Head of Business Improvements at the case company believe that one point of contact makes sense, but only if the person is responsible at the process level. If the SPOC were more deeply involved in subprocesses, this would mean too much detailed information and too much collaboration effort for one person. To track the qualitative and quantitative business value, alignment meetings should take place regularly and as a result of increased transparency through process mining. Regarding use-case prioritization, an *effort/impact matrix* evaluates the resources and the impact of each use case. We update lessons learned #4:

Adjusted lesson learned #4: Prioritize most value-driven use cases by establishing an effort/impact matrix for business value steering and setting up a SPOC to continuously orchestrate collaboration.

The last question considered business process knowledge and the method for leveraging process mining. The Director AR of the healthcare provider is confident with a *joint lab*. However, maintenance is needed to keep pace with developments within a company. While there is no joint lab at the healthcare provider, the technology group created a center of excellence (CoE) for process mining, which moderates between finance and IT. Both external interviewees emphasized that both knowledge and people should be selected in a broader sense, in order to spread knowledge across the organization. Thus, we enrich lessons learned #5.

Adjusted lesson learned #5: Spread knowledge proactively across the organization and gain a strong understanding of business processes within a centralized lab whilst combining a top-down use-case prioritization and a bottom-up user-story solution.

Then, the overall structure of the model was assessed by its *understandability* and its *completeness* [55]. Both external interviewees answered that the model is understandable, but not "self-explaining." They criticized the number of components: Two components could be sufficient, which could be prerequisites and process-mining-specific components. The drivers seemed to be complete, only the Head of Global Accounting suggested adding behavior to the category of capabilities. We come up with our sixth lesson learned.

New lesson learned #6: In order to keep things simple, you need to reduce the complexity of our model. In turn, we should consider adding employee behavior to the category of capabilities.

Regarding the *model's* **utility**, we asked if the interviewees would apply the recommended diamond model in other process mining use cases within and beyond Finance. The internal interviewees, as well as the Director AR of the healthcare product provider, agreed with this statement. The Head of Global Accounting of the technology group states that the operating model should be applicable in other business processes and explained that if one can abstract a concept, it can be applied effectively even beyond Finance. We derive the seventh and last lessons learned.

New lesson learned #7: Tailor the components of the proposed diamond model to the individual process environment, IT landscape, and the capabilities which are needed to perform process mining.

6 Discussion and Conclusion

The objective of this article was to develop *an operating model for process mining.* We referred to it as the diamond model. Starting with a literature review, we decided to conduct a DSR in IS study (Sect. 3) and cooperated with a science and technology company, which was our case company (Sect. 4). By conducting expert interviews, we tested our models' validity and utility (Sect. 5). Structured by the drivers and the associated enablers for process mining, our diamond model consists of eleven categories.

The seven lessons learned we finally presented should help practice and research as follows: **For practice**, our diamond model supports both gathering and prioritizing use cases for process mining as well as implementing and scaling this digital technology. Unlike approaches such as van Eck et al. [8], our model is not limited to process visualization and compliance but has a strong focus on a company's *business value creation*. So, we did not stop at the implementation of process mining, but we further presented ways for profitable business operations with our end-to-end solution.

With the drivers of our diamond model and the associated enablers of our diamond model, we overcame current challenges in process mining, such as missing commitment or internal resistance. While Kipping et al. [9] faced these challenges, they did not propose solutions to how to cope with them.

For research, our study extends the current status of literature by following the call for a process mining methodology where consideration of the organizational context and stakeholders' problems are reflected through all phases [56]. Furthermore, our operating model focuses on applying *agile methodologies* in contrast to prior work from van Eck et al. [8] and Aguirre [19]. Compared to Mans et al. [21], we extended their research by focusing more on *human-centric categories* whilst presenting our findings more simply and comprehensively. Finally, our research bridges the *gap between research and business* as we combined agile methodologies from practice with a literature review allowing better replicability of our lessons learned.

However, our research inevitably reveals certain **limitations** that open avenues for future research. Firstly, single case studies offer a broad range of advantages, but one critique is their *limited generalizability*. Thus, our research should become more multifaceted by examining other process mining domains beyond the O2C process such as smart accounts receivables management, or next use cases should apply predictive mining adopting machine learning algorithms. Process mining within other companies should be examined as well. For example, another avenue of future research might be to apply our model in human resource or supply chain processes inside and outside the case company to gain further insight into category completeness as well as context-specific prioritization of key categories. Accordingly, we will investigate the validity of the key categories identified in this study by opting for a field study, evaluating the rigor of our findings empirically, and translating our findings from descriptive to prescriptive guidance on how to implement and scale process mining for business value.

Although the general interest to leverage process mining technology was high within the case company, putting the ideas on hand into action requires experience and a sophisticated level of process and IS understanding. Accordingly, setting up training plans for employees is necessary. Finally, we need to continuously update our results, as the developmental pace of digital technologies is high.

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Appendix

Supplementary material for this work is available online (https://tinyurl.com/47asebxb):

Part 1 – result of literature review after outlet, database, and keyword search (limited to the last 10 years) yielding 25 hits

Part 2 – result of literature review including practitioner papers and after backward and forward searches yielding another 21 hits

Part 3 – result of the qualitative content analysis

Part 4 – coding rule used for qualitative content analysis

Part 5 – result of the quantitative analysis

Part 6 – documentation of evaluation interviews (incl. questionnaire)