Association for Information Systems

AIS Electronic Library (AISeL)

BLED 2019 Proceedings

BLED Proceedings

2019

Process Mining in The Rail Industry: A Qualitative Analysis of Success Factors and Remaining Challenges

Koen Smit

Joris Mens,

32ND BLED ECONFERENCE
HUMANIZING TECHNOLOGY FOR A SUSTAINABLE SOCIETY
JUNE 16 – 19, 2019, BLED, SLOVENIA, CONFERENCE PROCEEDINGS
A. Pucihar (ed. et al.)

Process Mining in The Rail Industry: A Qualitative Analysis of Success Factors and Remaining Challenges

KOEN SMIT & JORIS MENS

Abstract This paper aims to identify success factors and remaining challenges relevant to the practice of process mining in the rail industry. Process mining is a method for analyzing processes based on event logs. In a case study, we examine three process mining projects performed at the largest rail organization in The Netherlands. Experiences gained in these projects are compared to success factors specified in literature. The projects were analyzed using observations, secondary data collection and semi-structured interviews. We were able to identify all success factors specified in literature in the case study. In addition, several new success factors are identified. These concern challenges regarding the implementation of process mining software, intra-organizational knowledge sharing and continuous availability of event logs. For the additional success factors identified, it was not yet possible to determine if they are industry specific or generic in nature.

Keywords: • Process Mining • Business Process Management • Success Factors • Challenges • Rail Industry •

CORRESPONDENCE ADDRESS: Koen Smit, HU University of Applied Sciences Utrecht, Digital Smart Services, Utrecht, The Netherlands, e-mail: koen.smit@hu.nl. Joris Mens, NS Stations, Utrecht, The Netherlands, e-mail: joris.mens@ns.nl.

DOI https://doi.org/10.18690/978-961-286-280-0.36 ISBN 978-961-286-280-0
Dostopno na: http://press.um.si

1 Introduction

Business processes are among the most important assets of an organization. They must therefore be properly managed and controlled. The concept of a business process is defined by (Hammer & Champy, 1993) as: "*[...] a collection of activities that takes one or more kinds of input and creates an output that is of value to the customer.*" The management and control of business processes is referred to as Business Process Management (BPM), defined by (Weske, 2012) as: "*[...] concepts, methods, and techniques to support the design, administration, configuration, enactment, and analysis of business processes.*"

Several existing models describe capabilities required for proper BPM. Popular examples of these are 1) the Business Process Lifecycle (Weske, 2012), 2) the BPM cycle (Dumas, La Rosa, Mendling, & Reijers, 2013), 3) the Process Lifecycle (IBM Knowledge Center, 2018) or 4) the BPM framework (Jeston & Nelis, 2014). Business processes must be managed in an agile fashion to consistently add value in a changing environment. This includes redesigning and adapting processes to changing strategies or requirements. Most BPM models therefore include a cyclic approach for continuous improvement. Nearly all BPM models include a phase to analyze the as-is situation and use this as input for improvement of the business process. One way to analyze the as-is situation of a business process is Process Mining. Process Mining (PM) is defined as (van der Aalst & Weijters, 2004): "*the method of distilling a structured process description from a set of real executions.*" Possible key benefits of PM are its 1) objectivity, 2) bottom-up approach, 3) ability to simulate or predict based on process data, 4) visualization of process execution for stakeholders, and 5) ability to identify bottlenecks (Claes & Poels, 2012).

The current body of knowledge on PM shows many contributions focusing on the technical organization and implementation of PM. See for example (De Leoni, van der Aalst, & Dees, 2016; De Medeiros & Günther, 2005; De Medeiros & Weijters, 2005; Suriadi, Andrews, ter Hofstede, & Wynn, 2017; Tax, Sidorova, Haakma, & van der Aalst, 2016). To the knowledge of the authors, not many contributions focus on the success factors and remaining challenges regarding the implementation of PM in practice. The success factors and remaining challenges present in the current body of knowledge seem to be either generalized (Claes & Poels, 2012; Mans, Reijers, Berends, Bandara, & Rogier,

2013) or applied in industries other than the rail industry. See for example (De Medeiros, Weijters, & Van der Aalst, 2005; Homayounfar, 2012; Li, Reichert, & Wombacher, 2011). We aim to derive success factors and remaining challenges in the context of the rail industry and add these to the body of knowledge. This paper poses the research question: '*Which success factors and challenges regarding PM are relevant in the context of the Dutch Rail Industry?*'

The remainder of this paper is structured as follows. The next section describes the research background and related work regarding BPM, PM, and success factors and challenges relation to PM in the current body of knowledge and in practice. The section 'Research Method' elaborates and justifies the research approach. In the data collection and analysis section, the operationalization of the research method describes how the data was collected and analyzed by the research team. In the 'Results' section, the success factors and remaining challenges relevant to a large rail organization are presented. Based on this, the discussion, conclusion and future research directions are presented in the last two sections.

2 Background and Related Work

Although the body of knowledge on BPM features numerous quality frameworks that guide organizations in managing business processes, we adhere to the business process lifecycle framework of Weske (2012) (Figure 1). The framework describes how process mining is integrated within the practice of BPM.

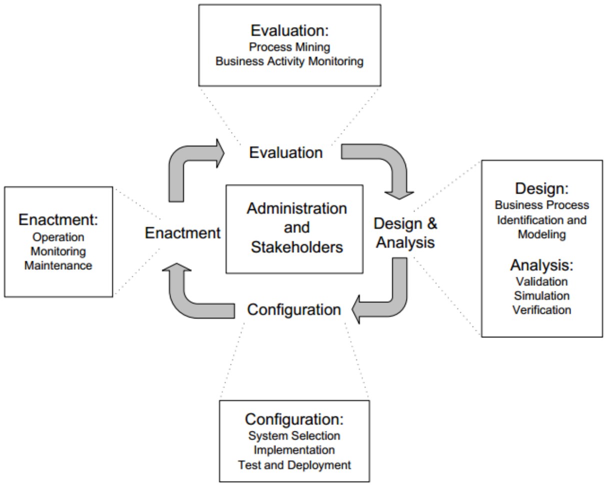

Figure 1: Business Process Lifecycle (Weske, 2012)

According to the Business Process Lifecycle, a business process undergoes several phases during its lifecycle and makes use of different concepts and technologies (Weske, 2012). When viewing the Business Process Lifecycle in Figure 1 in the context of PM, the phase 'Evaluation' stands out because it features PM as one of its key activities. It is important to note that PM also plays a central role in the design and analysis of business processes, as the identification and modelling of business processes are key benefits of PM (Claes & Poels, 2012). Additionally, van der Aalst, a leading researcher in the PM research domain, states that PM is a bridge between data mining and BPM (van der Aalst, 2011).

According to the Process Mining Manifesto, the goal of process mining is to discover, monitor and improve processes by extracting knowledge from event logs (Van Der Aalst et al., 2011). Event logs are the starting point for process mining and contain at minimum a case ID, an activity and a timestamp in order to algorithmically create process models (van der Aalst, 2012). Process mining capabilities are offered nowadays by both academic tools (e.g. PROM (Van Dongen, de Medeiros, Verbeek, Weijters, & van Der Aalst, 2005)), as well as commercial software (e.g. Celonis, Fluxicon Disco, ProcessGold) (Mans et al., 2013).

As described in the previous section, a significant number of contributions in the body of knowledge on PM have a technical orientation, while lacking the (organizational) adoption aspects of PM initiatives (de Schepper & Groeneveld, 2018). One way to examine PM adoption is to zoom in to success factors that contribute to adoption at organizations, and the challenges that are faced. To ground the discussion about (critical) success factors, a definition of a success factor is provided: "*those few things that must go well to ensure success for a manager or an organization, and, therefore, they represent those managerial or enterprise areas that must be given special and continual attention to bring about high performance.*" (Boynton & Zmud, 1984). In the context of this definition, we search for organizational challenges and success factors in the rail industry.

To discover challenges and success factors in the rail industry, we draw forth upon one key contribution in the field of PM regarding success factor identification. In their work, Mans, Reijers, Berends, Bandara, and Prince (2013), propose a model that comprises several PM as well as neighboring areas to consider in terms of (critical) success factor identification. The following areas need to be considered when identifying and analyzing success factors in the context of PM (Mans et al., 2013).

Project specific factors

- Management support: *The involvement and participation of senior management, and their ongoing commitment and willingness to devote necessary resources and time of senior managers to oversee the process mining efforts.*
- Project management: *The management of activities and resources throughout all phases of the process mining project, to obtain the defined project outcomes.*
- Resource availability: *The degree of information available from the project stakeholders during the entire process mining analysis.*

Process mining factors

- Process miner expertise: *The experiences of the person conducting the mining, in terms of event log construction, doing process mining analysis and knowledge of the business processes being mined.*

- Process mining approach: *The extent to which a process miner uses a structured approach during the entire process mining analysis.*

IS related factors

- Data & event log quality: *The characteristics of the raw data and subsequently constructed event logs.*

Several challenges regarding process mining still exist. Although many technical challenges have been overcome in the past years, e.g. challenges described in (Tiwari, Turner, & Majeed, 2008), many organizational challenges still seem to impact the outcomes of PM initiatives (Mans et al., 2013). The body of knowledge on PM, to the knowledge of the authors, does not contain contributions that identify or reflect upon challenges specifically regarding the rail industry. In other fields such as healthcare (Rojas, Munoz-Gama, Sepúlveda, & Capurro, 2016) or tourism (Lux & Rinderle-Ma, 2017), such studies do exist and are essential to reveal industry-specific challenges and success factors for process mining. For example, the work of Rojas et al., (2016) identified that one industry-specific aspect was hindering effective visualization of mined process models, which is that the healthcare domain features complex and less-structured processes. Our work is a first attempt to explore such (industry-specific) challenges regarding PM initiatives in the rail industry.

3 Research Method

The goal of this study is to reveal (industry-specific) success factors and remaining challenges regarding PM initiatives in the rail industry. The maturity of the PM research domain, regarding non-technological research, is nascent. In nascent fields, an appropriate focus involves identifying new constructs and establishing relationships between identified constructs (Edmondson & Mcmanus, 2007). Many researchers use explorative qualitative research methods to do so. We therefore conduct a qualitative study, using case study data collection and analysis to gather empirical evidence on success factors and open challenges. A case study approach helps us develop context-based descriptions of the phenomenon studied (Myers, 1997).

A single case study is utilized, further characterized by an embedded style design (Runeson & Höst, 2009). Within the context of the Dutch rail industry, one organization will be selected (the case) in which multiple PM projects (units of analysis) are evaluated against the success factor areas described in the previous section. This organization will be further referred to as 'the organization'.

4 Data Collection and Analysis

Data for this study was collected over a period of twelve months; from January until December 2018, through three PM projects at the organization. The case study features a multi-method approach, composed of 1) secondary data collection and analysis, 2) semi-structured interviews, and 3) observations. The selection of the participants in the case study should be based on the group of individuals, organizations, information technology, or community that best represents the phenomenon studied (Strauss & Corbin, 1998; Strauss & Corbin, 1990). For this study, the phenomenon studied is represented by organizations and individuals that deal with the planning, execution and evaluation of PM projects in the Dutch rail industry.

In the context of our study, a case was defined as a single process mining project aimed at the derivation of a model of a business process, with the end-goal of improving the business process. Improvement meaning the mitigation or removal of bottlenecks and/or increase conformance levels, among other factors.

The largest Dutch organization in the rail industry (in terms of FTE's and number of passengers) was selected for this research. The organization employs over twenty-thousand people and has a need to innovate and continuously improve business processes. These characteristics provided the best fit for selecting multiple 'mature' PM projects. The selection of cases was done in collaboration with the innovation team responsible for introducing process mining within the organization. The research team defines a 'mature' PM project as being completed recently (after January 2018) and involving the planning, execution and evaluation of a business process using PM. This criterion was defined because the organization performed multiple PM projects, however not all projects have reached the maturity deemed necessary to study the full spectrum of success factors.

The organization's innovation team is the primary team tasked with process mining projects at the organization and was therefore suitable for collaboration during this study. The innovation team consults other organizational departments on process mining practices and implementation.

The research team and the innovation team selected three projects that were deemed suitable for analysis in this study. The selected cases are described in detail in the Results section, followed by a presentation and mapping of success factors and remaining challenges regarding these projects. First, the data collection and analysis method is explained in the following sub-sections.

4.1 Observation

In the context of this study, observations were conducted as a data collection technique and as a project monitoring type. According to (Zelkowitz & Wallace, 1998), project monitoring type observation has no direct influence on the methods being used later and its data (mostly historical lessons learned) is solely utilized for some immediate analysis. One observation was performed for each PM project described in this paper. Observations were performed during an on-site visit at the department where the analyzed business process is performed, including a guided tour and explanation by an employee familiar with performing the process. Because the observer is an employee of the organization and not seen as an external researcher, this reduces the risk of introducing bias in the data collection from observation (Wohlin et al., 2012). The observations were performed by a member of the innovation team. Notes were taken to gather domain knowledge and to identify possible process bottlenecks to later study using process mining. Observation duration was at least one and a half hours per project.

4.2 Secondary data collection

Secondary data collection was used in addition to observations. Secondary data encompasses documentation produced during the execution of the PM projects. For each project, a Project Initiation Document outlines the goal, planning, and hypotheses for the respective project. At the end of each project, an advisory report presents the findings of project to the owner of the business process and describes lessons learned regarding performing the PM project. The PID is around five pages long and the advisory report around fifteen pages long. These documents were produced by a process mining expert within the innovation team.

4.3 Semi-structured interviews

Lastly, semi-structured interviews were utilized as a data collection technique. For each PM project, at least six meetings were organized with a bi-weekly frequency. Stakeholders in these meetings varied over time depending on what was discussed. Stakeholders included the process owner (usually a manager in the department), employees within the department, systems administrators, and database administrators. The duration of each interview was 45 minutes and notes were taken by members of the innovation team. These notes contain action points with regards to challenges regarding the PM project at hand as well as an evaluation of the project's progress.

4.4 Analysis

Due to the confidentiality of the data supplied by the organization, the analysis of the data was conducted solely by open coding, see also (Strauss & Corbin, 2015). Another limitation was that the data could only be analyzed on-site at the organization. With open coding, the researchers coded specifically on three aspects: 1) PM success factors (keeping in mind the definition of a success factor provided in section 2), the category (Mans et al., 2013) which the identified success factor belongs to, and 3) open challenges regarding PM. For example, some meeting notes included information regarding the difficulty of receiving data sets when the required business process logs are not locally accessible (from the department itself) and need to be accessed using a formal request, which takes a lot of time, thus hampering the project's progress.

5 Results

The case study encompasses three PM projects within the organization, performed in chronological order. After giving an outline of each process analyzed, we describe the success factors and challenges identified during these projects. These are mapped to the success factor categories specified in literature by (Mans et al., 2013). We conclude this section by describing the challenges that remain after the success factors are mapped to the model from literature.

Project A (Locker retention): A process mining project was conducted to analyze the ideal maximum retention time for luggage lockers. Customers can rent a luggage locker at the train station. A fee is charged per day of use, with a maximum of three days. Lockers still in use after the three-day limit are emptied by staff, and contents are held by the lost & found department. A late fee is charged to customers who eventually retrieve their belongings from this department. Emptying lockers and holding their contents is a labor-intensive and costly procedure. Process mining was used to determine if the operation of removing locker contents could be delayed, thereby reducing the number of times this operation must be performed. It was found that for most late lockers, the contents are eventually retrieved by the customer within ten days. Delaying the emptying of late lockers up to ten days saves considerable time and resources by staff from the lost & found department. Meanwhile, the customer can still be charged a late fee through the locker management system.

This process is relatively simple and includes a limited number of activities and possible process paths. Process mining was used mainly because its time-sensitive nature allows us to test hypotheses related to deadlines, such as overdue rental periods.

Project B (Service desk): The organization's service desk is responsible for coordinating the (unplanned) maintenance and repair of assets in train stations (such as escalators, elevators and lighting) as well as structural parts of the station building (windows, roofing, etc.). The service desk coordinates several contractors to carry out repair & maintenance activities, who are bound to completion timeframes through an SLA. Process mining was performed to find out (1) if contractors were completing their work within the set timeframe, (2) if there were superfluous fields/activities in the service desk's software that could be eliminated, and (3) which method of requesting repairs at the service desk provides the shortest lead time (e-mail, app, or telephone). Based on the findings of the project, some SLAs were renegotiated, and an optimized process was implemented when the department transitioned to a new version of their software.

This process is characterized by high complexity and unpredictability because of the unplanned nature of the interruptions. The process involves a large variety of parties performing human tasks.

Project C (Wheelset overhaul): The organization's technical workshop performs the process of overhauling train wheelsets. This process involves removing the steel wheels from the axle, re-profiling the wheels, performing several tests and applying protective paints before the wheelset is reassembled. This process was recently modernized using a robotized production line to improve the quality, precision, and safety of the overhaul. Because the production line is relatively new, some teething problems occurred. Thanks to process mining, it was found that some stations in the production line could cause unexpected delays. These stations were then deployed in parallel configurations so that delays would not cause backing up of the entire production line.

The process is characterized by being relatively straightforward, with a set order of a activities in the production line. The process is highly automated with few human tasks and produces detailed event logs for process mining.

5.1 Success factors for process mining in practice

In this sub-section we describe to which extent the success factors identified in literature were present in the process mining projects described above. This helps us to identify how these success factors have influenced these projects, how the organization can improve its success factors and which challenges remain.

- Management support: Management support for process mining was high in all projects, since it was identified as one of the technological trends that the organization wants to invest time and resources in. This allowed the innovation team to gain experience and perform multiple projects.
- Project management: The team applied project management techniques already present at the organization and was successful in obtaining the defined project outcomes. However, due to the specific nature of process mining projects, new skills had to be learned to perform project management in these projects successfully.

- Resource availability: Resource availability was decent, since the necessary stakeholders were willing to contribute their knowledge to the product. This is because specific problems faced by the stakeholders were the reason for initiating the process mining projects. They were therefore intrinsically motivated to achieve the end-goal of the project. More difficulty was faced in identifying and extracting the necessary data for process mining, as this was a new type of information that wasn't normally requested in the organization.
- Process mining expertise: PM expertise was gained by following a formal training course with a supplier of process mining software and gaining experience by performing process mining projects. The expertise grew over time.
- Process mining approach: The team applied a structured approach using. However, over time more experienced was gained in how to specifically acquire and extract the necessary data for process mining. Therefore, the process mining approach became more structured as more projects were performed.
- Data & Event log quality: Data quality was mixed. Gathering the correct data and 'grooming' it into a suitable format was one of the biggest challenges of the projects described. On a technical level, not all systems initially recorded the necessary data to create an event log or the data was cumbersome to access and extract. On a functional level, meetings with stakeholders were needed to interpret the data and to find out which activity in the 'front-end' of the process resulted in which 'back-end' logging of the activity, to give meaning to the process models that were mined.

For mapping the practical experiences describe above with success factors to those found in literature, we classify the presence of these factors in each project into three categories in Table 1 below. These categories are 'low', 'moderate', and 'high'. Low meaning that the success factor was barely or not at all present during the project, 'Moderate' meaning that the success factor was identified but not to the full extent described in the model, and 'High' meaning that the success factor was fully identified.

Table 1: Extent of success factor identification in case study projects

	Project A	Project B	Project C
Project specific factors			
- Management Support	High	High	High
- Project Management	Moderate	Moderate	High
- Resource Availability	Moderate	Moderate	High
Process Mining Factors			
- Process Miner Expertise	Moderate	Moderate	High
- Process Mining Approach	Moderate	High	High
IS Related Factors			
- Data & Event Log Quality	Moderate	Moderate	High

Remaining challenges

After discussing the success factors and how they were found in practice, challenges regarding process mining remain. We outline these challenges as follows:

- Availability and characteristics of process mining software: Process mining software is required to perform PM analyses. A large variety of software packages is available on the market. These have differing software architectures, such as a standalone desktop application, or SaaS applications which perform process mining in a cloud-based environment. To assess which software best fit the needs of the organization, several such solutions were tested. It was found that some SaaS-solutions focus specifically on continuous monitoring of business processes by connecting directly with back-end databases. Since our projects were focused more on analyzing a post-hoc dataset manually extracted from a database, we found more use in a flexible standalone desktop application. Selection of process mining software is also influenced by architectural constraints within the organization's IT landscape. Another challenge was finding a suitable licensing scheme for the organization, where the need for process mining software scaled up or down over time. In conclusion, organizations will need to consider how process mining software fits into their overall application landscape and any IT-related policies that may apply. Organizations will need to consider which licensing scheme best fits their needs and financial constraints, with suppliers offering for example, per-user or per-process licensing schemes.

- Knowledge building and knowledge-sharing: In a large organization such as the organization studied in this paper, knowledge sharing between departments is challenging. In earlier years, it was found that different departments were exploring process mining on their own, without necessarily having knowledge of other PM initiatives within the organization. This led to a variety of process mining software being purchased without a centralized vision, as well as differing policies regarding data availability. In recent months a centralized innovation portal was launched which helps mitigate this problem by listing process mining as one of the key technological trends within the organization. Existing process mining projects, articles, and expert contact information is published in this portal, allowing for increased knowledge propagation. Depending on their characteristics, organizations must find a suitable way to make sure process mining knowledge is secured and propagated to gain the most benefit from their efforts.

- Availability and distribution of event logs: Another challenge faced is that for each process mining project performed, many manual steps were needed to identify and extract the necessary data for process mining. This is caused by each system having its own method of logging event data, with different levels of granularity and suitability for mining. Policies for accessing this data differ, depending on data confidentiality and ownership. To overcome these challenges, the solution is two-fold: (1) When designing system requirements for new or changing systems, event logging must be integrated to ensure availability and enable easier extraction when needed. (2) Event logs should be distributed through a centralized portal, so that they are easily acquired in a suitable format.

> We have seen one such solution used in practice at another organization, where end-users could download event logs from several systems through a portal. This eliminates the many manual steps in acquiring process mining data.

The remaining challenges identified in this case study were not yet identified in literature, and therefore extend the set of possible success factors. The next sections describe limitations of this study, future research directions and the implications of these findings.

6 Discussion and Future Research

As is the case with all empirical research, this research has its limitations. The first limitation concerns the generalizability of the identified success factors and challenges toward the entire organization as well as the Dutch rail industry. The generalizability towards the organization is grounded by the fact that the innovation team involved in this study are part of many PM projects throughout the organization. Therefore, as the organization is by far the largest organization in the rail industry in the Netherlands, the results are partly generalizable towards the Dutch rail industry. Future research must include results from more organizations in this industry to be able to analyze a larger dataset before generalization can be achieved.

Although this study features three cases with varying characteristics, the research team could not identify rail industry-specific success factors or challenges. This does not imply that rail-specific factors are completely nonexistent in the organization or in the entire rail industry. Such success factors and challenges are context dependent, which should also be investigated in future research. The processes selected in this case study are a locker rental process, a service desk process and a technical overhaul process. While these process are performed within a rail organization specifically, it can be said that such processes are not unique to the rail industry and similar processes are possibly present in other (transport) industries. This may limit the extent to which the identified success factors and challenges are specific to the rail industry.

The possibility for future research into success factors and challenges is made evident by the fact that the current body of knowledge on PM has a predominant focus on technical capabilities and lacks information on organizational capabilities regarding PM implementation and adoption. The current body of knowledge does not contain many empirical studies that focus on success factors and challenges regarding specific industries. A final interesting direction for future research is why some PM projects fail to reach maturation or continuously add value to the process. Future research should focus on how process mining can be more structurally embedded in process improvements methods of the organization.

7 Conclusion

The goal of this research was to answer the following research question: "*Which success factors and challenges regarding PM are relevant in the context of the Dutch Rail Industry?*" To do so, an embedded case study was applied at the largest organization in the Dutch rail industry. To ground the identified success factors, the PM success factor model of (Mans et al., 2013) was utilized. The results show that the organization has process mining on the R&D agenda and has sufficient management support. Because of this, resources were allocated to explore and execute PM projects throughout the organization. Data quality is mixed at the organization to affect the efficiency of PM initiatives, which is similar to experiences regarding data quality of PM projects in the body of knowledge. Also, one contingency factor seems to affect the efficiency and effectiveness of PM projects, which is the size of the organization. Large organizations are prone to initiate several isolated PM initiatives without intra-organizational knowledge propagation. The organization studied found that a central knowledge portal that tracks PM projects proved effective in creating awareness and sharing knowledge among different departments.

It seems that using the success factor model from literature in combination with data collection and analysis of the selected cases did not yield any industry-specific success factors or challenges. It appears that the extent in which these factors are encountered depends more on other properties such as the size or culture of the organization or the characteristics of the process analyzed.

The research yielded three additional challenges that were not specifically mentioned in the PM success factor model of (Mans et al., 2013). These challenges concern 1) the characteristics of process mining software such as licensing schemes and the ability of the software to fit into the organizational IT landscape and policy constraints, 2) Applying knowledge management practices to secure and propagate knowledge on process mining within the organization, and 3) incorporating event logging in the design of information systems, as well as making event logs available through a centralized portal for increased ease of access. Overcoming these challenges may lead to additional success factors that contribute to achieving the desired goals of process mining projects.

References

Boynton, A. C., & Zmud, R. W. (1984). An assessment of critical success factors. Sloan Management Review, 25(4), 17–27.

Claes, J., & Poels, G. (2012). Process mining and the ProM framework: an exploratory survey. In International Conference on Business Process Management (pp. 187–198). Heidelberg: Springer, Berlin.

De Leoni, M., van der Aalst, W. M. P., & Dees, M. (2016). A general process mining framework for correlating, predicting and clustering dynamic behavior based on event logs. Information Systems, 56, 235–257.

De Medeiros, A. A., & Günther, C. W. (2005). Process mining: Using CPN tools to create test logs for mining algorithms. In Proceedings of the sixth workshop on the practical use of coloured Petri nets and CPN tools.

De Medeiros, A. A., & Weijters, A. J. M. M. (2005). Genetic process mining. In Applications and Theory of Petri Nets 2005.

De Medeiros, A. A., Weijters, A. J. M. M., & Van der Aalst, W. M. P. (2005). Genetic process mining: A basic approach and its challenges. In International Conference on Business Process Management (pp. 203–215). Heidelberg: Springer, Berlin.

de Schepper, D. J. J., & Groeneveld, B. S. N. H. (2018). Determining success factors for process mining initiatives. Tilburg.

Dumas, M., La Rosa, M., Mendling, J., & Reijers, H. A. (2013). Fundamentals of business process management. Heidelberg: Springer.

Edmondson, A. C., & Mcmanus, S. E. (2007). Methodological Fit in Management Field Research. Proceedings of the Academy of Management, 32(4), 1155–1179.

Hammer, M., & Champy, J. (1993). Re-engineering the Corporation; A Manifesto for Business Revolution. New York: Harper Business.

Homayounfar, P. (2012). Process mining challenges in hospital information systems. In Federated Conference on Computer Science and Information Systems (pp. 1135–1140). IEEE.

IBM Knowledge Center. (2018). Business process management overview. Retrieved March 15, 2019, from https://www.ibm.com/support/knowledgecenter/en/SS8JB4_18.0.0/com.ibm.wbpm.workflow.main.doc/topics/gettingstarted_landingpage.html

Jeston, J., & Nelis, J. (2014). Business process management. Routledge.

Li, C., Reichert, M., & Wombacher, A. (2011). Mining business process variants: Challenges, scenarios, algorithms. Data & Knowledge Engineering, 70(5), 409–

434.

Lux, M., & Rinderle-Ma, S. (2017). Problems and Challenges When Implementing a Best Practice Approach for Process Mining in a Tourist Information System. In BPM 2017 (pp. 1–12).

Mans, R., Reijers, H., Berends, H., Bandara, W., & Rogier, P. (2013). Business process mining success. In Proceedings of the 21st European Conference on Information Systems. AIS Electronic Library (AISeL).

Myers, M. D. (1997). Qualitative research in information systems. Management Information Systems Quarterly, 21(2), 241–242.

Rojas, E., Munoz-Gama, J., Sepúlveda, M., & Capurro, D. (2016). Process mining in healthcare: A literature review. Journal of Biomedical Informatics, 61, 224–236.

Runeson, P., & Höst, M. (2009). Guidelines for conducting and reporting case study research in software engineering. Empirical Software Engineering, 14(2), 131–164.

Strauss, A. & Corbin, J. (1998). Basics of qualitative research, Second edition. Thousand Oakes.

Strauss, A., & Corbin, J. (2015). Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory. Basics of Qualitative Research Grounded Theory Procedures and Techniques (3rd ed., Vol. 3). Thousand Oaks, CA: SAGE Publications Ltd. https://doi.org/10.4135/9781452230153

Strauss, A., & Corbin, J. M. (1990). Basics of qualitative research: Grounded theory procedures and techniques. Sage Publications, Inc.

Suriadi, S., Andrews, R., ter Hofstede, A. H., & Wynn, M. T. (2017). Event log imperfection patterns for process mining: Towards a systematic approach to cleaning event logs. Information Systems, 64, 132–150.

Tax, N., Sidorova, N., Haakma, R., & van der Aalst, W. M. P. (2016). Event abstraction for process mining using supervised learning techniques. In Proceedings of SAI Intelligent Systems Conference (pp. 251–269). Cham: Springe.

Tiwari, A., Turner, C. J., & Majeed, B. (2008). A review of business process mining: state-of-the-art and future trends. Business Process Management Journal, 14(1), 5–22.

van der Aalst, W. M. P. (2011). Process Mining. Berlin: Springer.

Van Der Aalst, W. M. P., Adriansyah, A., De Medeiros, A. K. A., Arcieri, Baier, F., Blickle, T., & Burattin, A. (2011). Process mining manifesto. In International Conference on Business Process Management (pp. 169–194). Heidelberg: Springer, Berlin.

van der Aalst, W. M. P., & Weijters, A. J. M. M. (2004). Process mining: a research agenda. Computers in Industry, 53(3), 231–244.

Van Dongen, B. F., de Medeiros, A. K. A., Verbeek, H. M. W., Weijters, A. J. M. M., & van Der Aalst, W. M. P. (2005). The ProM framework: A new era in process mining tool support. In International conference on application and theory of petri nets (pp. 444–454). Heidelberg: Springer, Berlin.

Weske, M. (2012). Business Process Management. Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-28616-2

Wohlin, C., Runeson, P., Höst, M., Ohlsson, M. C., Regnell, B., & Wesslén, A. (2012). Experimentation in software engineering. Springer Science & Business Media.

Zelkowitz, M. V., & Wallace, D. R. (1998). Experimental models for validating technology. Computer, 31(5), 23–31.