From Process Mining Insights to Process Improvement: All Talk and No Action?

Vinicius Stein Dani[1](✉), Henrik Leopold[2], Jan Martijn E. M. van der Werf[1], Iris Beerepoot[1], and Hajo A. Reijers[1]

[1] Utrecht University, Princetonplein 5, 3584 CC Utrecht, The Netherlands
{v.steindani,j.m.e.m.vanderwerf,i.m.beerepoot,h.a.reijers}@uu.nl
[2] Kühne Logistics University, Großer Grasbrook 17, 20457 Hamburg, Germany
henrik.leopold@the-klu.org

Abstract. Organizations from various domains use process mining to better understand, analyze, and improve their business processes. While the overall value of process mining has been shown in several contexts, little is known about the specific actions that are taken to move from process mining insights to process improvement. In this work, we address this research gap by conducting a systematic literature review. Specifically, we investigate which types of actions have been taken in existing studies and to which insights these actions are linked. Our findings show that there exists a large variety of actions. Many of these actions do not only relate to changes to the investigated process but also to the associated information systems, the process documentation, the communication between staff members, and personnel training. Understanding the diversity of the actions triggered by process mining insights is important to instigate future research on the different aspects of translating process mining insights into process improvement. The insights-to-action realm presented in this work can inform and inspire new process mining initiatives and prepare for the effort required after acquiring process mining insights.

Keywords: Process mining · Insights to action · Process improvement · Systematic literature review

1 Introduction

Process mining techniques allow organizations to obtain insights that help them improve their processes [55]. The core idea of process mining is to exploit so-called *event logs*. These event logs are extracted from different IT systems that are used throughout the organization and, therefore, reveal how processes are actually executed [2]. Process mining has been successfully applied in various domains, including healthcare [45], auditing [28], and supply chain management [30].

Despite the success and popularity of process mining in practice, there is a limited understanding of how process mining insights eventually lead to process

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improvements. Specifically, it is unclear which *actions* organizations can consider based on the insights they have obtained through process mining. Existing process mining methodologies (e.g. [17]) provide structured guidance on how to use process mining to obtain relevant insights. However, they do not provide details on how to translate these insights into process improvements. We argue that understanding this *realm of actions* is a valuable aspect to complement existing process mining methodologies. By understanding which actions toward process improvement can be taken and how they are connected to the obtained insights, organizations can more easily identify the best path toward process improvement.

Against this background, we use this work to address the following research question: "*What are the actions organizations can take towards process improvement and how are they connected to process mining insights?*". To answer our research question, we conduct a systematic literature review. Based on the identified literature, we first investigate the different actions that are recommended or performed by process mining projects. Second, we investigate which insights lead to specific actions. Finally, we derive an overview of the actions triggered by process mining insights. Our contribution, therefore, is a systematic overview of actions, insights, and their connection. What is more, we identify the *intervention space*, i.e., the aspects of the organization that are affected by the actions, since process improvements actions may not only concern the process itself.

The remainder of this paper is structured as follows. In Sect. 2, we present the background and highlight the research gap. In Sect. 3, we describe our research method. In Sect. 4, we report our findings. In Sect. 5, we provide a reflection on our findings and, finally, Sect. 6 concludes the paper.

2 Background

In this section, we introduce the background for our work and highlight the research gap. First, we briefly explain what process mining is and what it offers to organizations. Second, we elaborate on process mining methodologies, i.e. works that specify which steps organizations need to take to successfully apply process mining. Third, we discuss the relationship between process mining and process improvement and argue that there is a missing link between the two.

Process Mining. Process mining is a family of techniques that facilitate the analysis of business processes based on so-called event logs [1,55]. These event logs are extracted from different types of information systems that support the process execution and are usually captured using the dedicated and standardized format XES [61]. It is important to highlight that event logs are not available per se and that the extraction of event logs from information systems may require considerable manual effort [57]. Once an event log is available, different types of analyses can be performed. The three most prominent process mining use cases in practice include process discovery, conformance checking, and enhancement [1]. The goal of process discovery is to generate a process model from the given event log that appropriately captures the as-is process. In conformance checking, a normative process model (capturing the desired process) is compared against the event log to detect deviations. Enhancement relates to a variety of use cases where a process model (e.g., discovered by means of process discovery) is enriched with additional information such as execution time, resources, or costs. Among others, this facilitates predictions related to the remaining execution time or the chances of successful process completion.

Process Mining Methodologies. Different process mining methodologies have been developed [1,9,15] with the goal of supporting process mining initiatives in practice. They typically outline specific steps, such as defining scope, collecting data, applying process discovery or conformance-checking techniques, analyzing results, and improving processes. Although these methodologies generally follow a similar high-level flow, they often do not provide specific guidance on how to translate process mining insights into process improvements [17] nor do they outline the different actions that *could* be used to follow up on the obtained insights.

The authors of the Process Diagnostics Methodology [9] recognize the importance of the recommendation phase (i.e., results transfer) of a process mining project. However, they make clear that it is the organization's responsibility to interpret and take action based on the acquired process mining insights. Although the authors of PM^2 [15] recognize the importance of the process improvement phase, they argue that this is usually part of a separate project. The authors of L* [1] propose improvement actions (e.g., redesigning, intervening) to follow up on the acquired insights. However, they do not provide much details about these actions.

Process Mining for Process Improvement. A key driver behind the application of process mining for many organizations is the desire to improve their business processes. However, successfully using process mining for process improvement comes with several challenges. Recognizing this, several studies investigate how process mining is implemented and, among others, identify key success factors [41] and key challenges for the adoption of process mining [32,42].

Other studies also more explicitly focus on the link between process mining and process improvement. For example, Eggers et al. [16] investigate how process mining can support improving process awareness in organizations. They identify seven mechanisms related to achieving increased process awareness pertaining to, for example, the inter-individual process level (i.e., when stakeholders share awareness of their sub-process within one department) or the inter-functional process level (i.e., when stakeholders share awareness of the end-to-end process across different departments). Lashkevich et al. [35] develop an analysis template to support identifying improvement opportunities based on process mining insights systematically. In their paper, they provide an example of a template relating to bottleneck analysis.

What is currently still missing is a comprehensive understanding of the actions that can be used to follow up on process mining insights. We believe that making these actions explicit can help organizations to understand the different options they can consider and, in this way, complement existing process mining methodologies.

3 Research Method

To answer our research question, we conducted a systematic literature review according to [33,48], which involves four main stages: 1) literature review protocol definition, 2) study selection and data extraction processes execution, 3) data analysis, and 4) reporting. To ensure reproducibility, we involved several authors in these four stages. Three of the authors were involved in defining the literature review protocol. The search string and exclusion criteria were applied via the search engines by one of the authors, as defined in the review protocol. The inclusion criteria were defined and applied by two authors independently. Finally, two authors conducted the data extraction while discussing with the other authors the derivation of codes and themes reported in Sect. 4. We resolved disagreements through discussions among the authors. Below, we discuss the first three stages of our literature review. In Sect. 4, we report our findings.

3.1 Literature Review Protocol Definition

In this stage, we defined the research question and the study selection and data extraction processes. We were particularly interested in identifying which actions are performed after process mining insights have been acquired.

Based on our research question, we defined the following search string: "(process mining) AND ('case study' OR 'case studies') AND (application OR apply OR applied)", to focus on process mining application and not in, for example, the implementation of a new process discovery technique. Then, inspired by other literature review studies in the process mining field [55,65], we defined the following set of search engines to apply our search string on: ACM Digital Libray, IEEE Xplore, Science Direct, Scopus, and Web of Science. We did consider including Springer Link in the set of search engines. Still, based on a pilot run of our study selection process, we identified that it would only add duplicates to the papers retrieved by the other search engines.

We defined exclusion and inclusion criteria to support our study selection process composed of four main stages: 1) application of search string into search engines, 2) application of exclusion criteria, 3) removal of duplicates, and 4) application of inclusion criteria. A study selection process of a systematic literature review determines how the exclusion and inclusion criteria will be applied to derive the final set of papers to be fully read [33]. The following exclusion criteria were defined: a) the paper is not written in English, b) the paper is not a conference paper, journal, or book chapter, c) the paper is not from computer science, decision sciences, business, management and accounting, healthcare, or social sciences. We further defined the following inclusion criteria: a) the paper is about the application of process mining or the use of process mining in a case study and b) the paper discusses what happens with process mining insights after they have been acquired.

The studies conforming to both inclusion criteria were kept and then further analyzed in the study selection and data extraction stage (cf. Sect. 3.2). The exclusion criteria supported us in filtering out papers directly from the search engines and the inclusion criteria supported us in deciding which papers were to be fully read, via a three-step application of the inclusion criteria, further detailed in the next section.

3.2 Study Selection and Data Extraction

Figure 1 presents our study selection process and shows the number of papers obtained from the execution of each stage. We applied the search string to the search engines, applied the exclusion criteria to the resulting papers, and removed duplicates. Then, we applied the inclusion criteria via a three-stage screening of the remainder papers: first, we screened the papers' titles and keywords (and their abstracts, when it was not yet clear if the paper should be excluded); second, we screened the abstracts of the remaining papers (and, in some cases, the conclusions); third and, finally, we screened the conclusions (and, in some cases, the methodology or the full text) to then reach to the final set of 57 selected papers to be fully read.

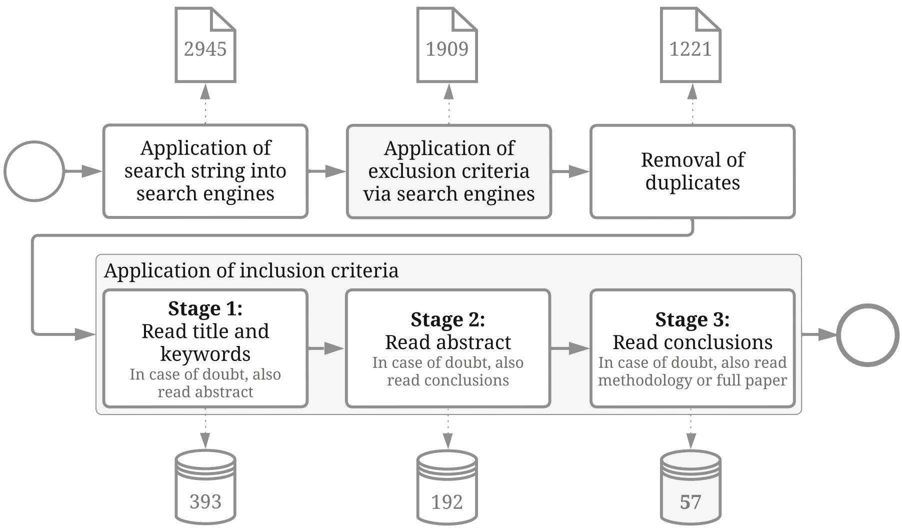

Fig. 1. Study selection process with number of papers yielded per stage.

For the data extraction process, we imported the complete list of 57 selected papers into an evidence table where we kept track of the following features extracted from each paper: reported insight, quote (from which the action was coded), coded action (i.e., what happened -or was recommended- triggered by the reported insight), action sphere (i.e., the coded action was either performed or recommended).

3.3 Data Analysis

We conducted an inductive content analysis with open coding, inspired by [53], to make sense of the extracted data from the selected papers resulting from our study selection process. The generated codes were grouped into different higher-level categories. The themes naturally emerged from the categories. In Sect. 4, we present the themes, categories, subcategories, and codes derived from the selected papers of our literature study.

While performing the coding of the quotes extracted from each of the 57 selected papers, the codes naturally assumed the format *verb* + *object*, which then enabled us to categorize our findings in terms of "actions" (verbs) and "intervention space" (composed by objects target of the actions). An example of a code that emerged from our open coding is "update documentation" where we have the *verb* "update" and the *object* "documentation". Because of the high amount of different verbs related to the same objects (e.g., information system, process case, etc.) of the intervention space, we identified a clear pattern pointing out the important role the objects target of the actions themselves play in understanding the realm of actions related to translating process mining insights into process improvement.

In total, 156 quotes related to what happened with process mining insights after they had been acquired were extracted from the 57 papers fully read. Because each quote may derive one or more codes, summing up all supporting quotes for each category leads to a total of 226 supporting quotes. For example, we derived the codes "justify conduct" and "clarify conduct" out of the following quote from [40]: "*The use of both manual and online document approval by the director needs to be justified and clarified whether it will be a permanent practice* (...)". As another example, the codes "identify data quality issues" and "adjust data quality issues" were derived out of the following quote: "*The business improvement team will use the conformance checking results to identify and rectify potential* (...) *data quality issues*" [39].

4 Findings

In this section, we present the findings of our paper. In Sect. 4.1, we first provide a high-level overview. In Sects. 4.2 through 4.4, we then take a detailed look into three themes we identified and discuss the specific actions for each theme. Finally, in Sect. 4.5, we discuss the most recurrent insights and the actions they trigger.

4.1 Overview

Studies reporting on what organizations do after they have acquired insights through process mining refer to both actions performed and recommended (i.e., actions to be performed). In this paper, to develop an overview of the realm of actions that can be triggered by process mining insights, we consider both kinds of reported actions simply as "action". The rationale behind this decision is that the recommendations are made by experienced professionals in the field and, therefore, can be considered as feasible. As a result, we identified three main themes of actions: i) supporting process understanding and documentation; ii) improving the involved information system supporting the investigated process; and iii) improving the investigated process. Each theme refers to one or more *intervention spaces*, such as *analysis* or *documentation*.

Figure 2 summarizes our results visually. It shows the main themes (dark gray), the intervention spaces (light gray), and the objects (white background) that are related to the intervention space. The numbers attached to the intervention spaces and the objects reveal the total number of supporting quotes from the analyzed papers. While these numbers should not be interpreted as a relevance factor, they do indicate how frequently a certain intervention space or object is the subject of an action after a process mining analysis.

In the next sections, we discuss each theme in more detail and provide a snapshot with respect to the identified actions.

4.2 Supporting Process Understanding and Documentation

This theme contains actions related to three intervention spaces: analysis, documentation, and communication and training. Next, we discuss each intervention space in detail.

Analysis. This intervention space contains actions related to different flavors of investigation that can be triggered by process mining insights. Several studies report on conducting or specifying follow-up investigations [5,25,29]. As an example, consider the domain expert checking if the identified relationships among members of collaboration groups match the designed procedures [29]. Other studies report on simulating or testing recommended proposed changes [8,25,43,51]. Other kinds of follow-up investigation are related to investigating or discussing root-causes of the insights [3,11,64]. For example, in [11], the authors investigated the causes of a high ticket resolution time variance. Studies also report on investigating causality or correlation [5,49,52]. In [52], the authors investigated the causal relation between two different activities of interest, while in [5], the authors investigated (alongside experts) the correlation between the involvement of specific organizational units and the process performance achievement. Studies also reported on clarifying or justifying conduct related to unexpected behavior in process cases [40,52], reviewing performance indicator [64], deriving background arguments to support decision making [22,44] and deriving improvement initiatives [4,14,40].

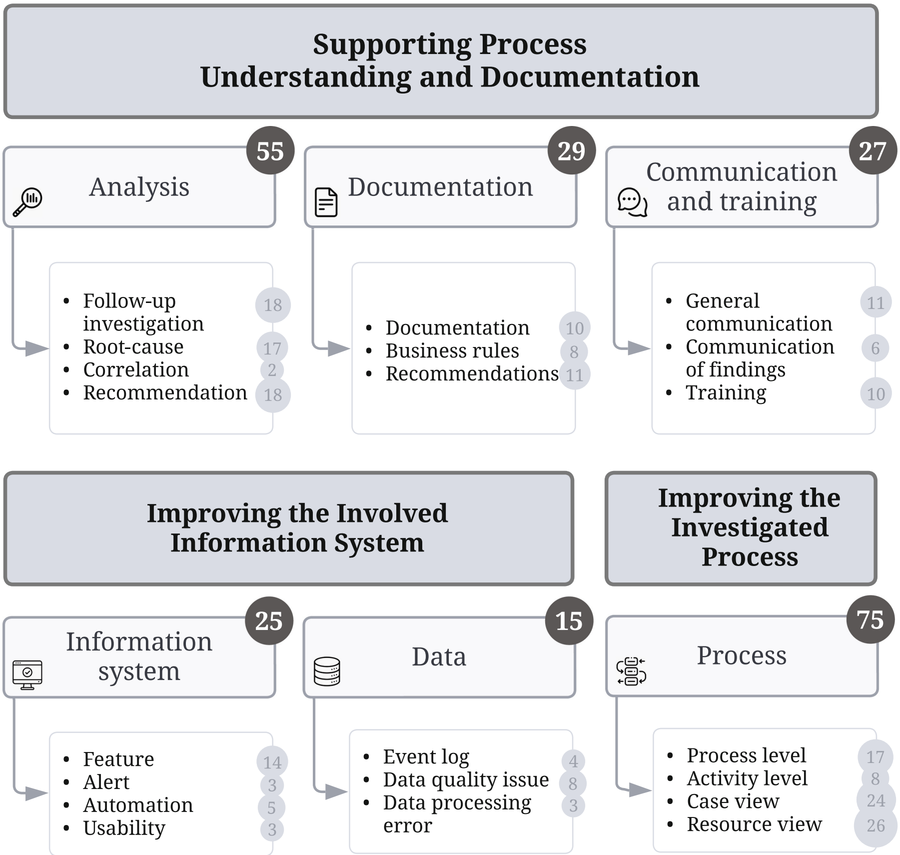

Fig. 2. Themes and intervention spaces of actions triggered by process mining insights as reported in the literature.

Documentation. This intervention space contains actions directed at the documentation itself, business rules within a documentation, and reports (i.e., a specific type of documentation that will be used to report on process mining findings). Actions related to the documentation itself include: creating, reviewing, updating, and improving a documentation [6,39,47] or using specific techniques to organize information (e.g., ontologies) to add up to a documentation [6]. In [39], the authors mention that the directly-follows graphs were used to document processes with outdated or missing documentation. Regarding business rules and documentation, there are papers that refer to isolating, adapting, or reviewing business rules [11,22,28]. For example, in [28], the authors mention the need to review business rules in the sense of checking if they are being enforced. In addition, other papers refer to adjusting service level agreements [50,56] based on process mining insights. Finally, regarding reporting, papers refer to writing, sharing, and presenting a report with the acquired insights [38,46,49], as well as formulating recommendations to be added to the report [25].

Communication and Training. This intervention space contains actions concerned with communication, information sharing, and training. Actions regarding communication include challenging conventional beliefs, increasing awareness about the process, or creating an ad-hoc custom visualization for communicating findings [22,36,46]. Regarding information sharing, reported actions are related to providing feedback on performance measurements [3,27]. For example, in [3], the authors provide feedback regarding specific detected loops in the process under investigation. Other papers report on discussing the likelihood of partial findings [46,52], informing the manager about specific findings [3], or improving information sharing [5,52,64] to, for example, improve coordination between collaborating stakeholders [64]. Training may be used to reinforce internal controls or good practices [62,63]. Other studies report on conducting training for staff members [20,47,63] leading to, for example, quality improvement, or reducing the need to perform a specific corrective activity [47]. Also, the discussion of potential training issues [39] was reported as an action triggered by process mining insights.

4.3 Improving Involved Information System

This theme contains the actions related to two intervention spaces: information system and data. Next, we discuss each intervention space in detail.

Information System. This intervention space contains actions directed at the information system(s) of the organization. They include creating, introducing, or testing a new feature [12,22,24,40], testing or improving test scripts of a feature [52], or simply using existing features [5]. For example, in [40], the authors used process mining in the context of the adoption of a new Enterprise Resource Planning system. Based on the insights, they identified the need to reinforce testing new features to ensure they behave as expected. Other papers report on adjusting feature settings [11,34,37], creating alerts [23,28], improving system usability [52,60], identifying automation opportunities [7,21], and adopting or implementing automation [18,50,63]. For example, in [21], the authors report on identifying automation opportunities by calculating the ratio between cases in which an activity was executed by a user and the total number of instances of the activity under investigation.

Data. This intervention space contains actions directed at the event log. They include filtering or re-collecting the event log [4,24,54], as well as identifying or rectifying data quality issues [39,54,59,63]. In [63], the authors reported deriving recommendations for improving data quality issues of the event log based on the argument that the input data quality interferes with the quality of a process mining project. They recommended, for example, the verb-object naming style for activities and keeping track of both start and end timestamps of activities, as these are helpful for process analysis. Other papers report identifying, reviewing, or rectifying data processing errors [39,64]. For example, in [39], the authors discuss that the business improvement team would use conformance checking-related insights to identify and rectify data processing errors and data quality issues. Note that the actions related to identifying or reviewing could also fit into the intervention space "Analysis". However, because the papers explicitly discuss these actions being directed at the event log itself, we included them in the "Data" intervention space.

4.4 Improving the Investigated Process

This theme represents the intervention space that contains actions toward the process. These actions can be more generic, such as redesigning, simplifying, changing, or standardizing the process [14,19,24,40]. However, the actions can also be more specific toward a particular aspect of the process, such as isolating or checking potential deviation in cases [28,29]. The actions can also refer to analyzing process cases [18,27,39] such as in [18], where the authors report on analyzing process cases containing high time-consuming tasks [18] or, as in [29], where the authors report on analyzing process cases from a resource perspective.

Some papers refer to actions directed at activities, such as parallelizing, removing, increasing the frequency of, or limiting, preventing or postponing the execution of an activity [5,10,13]. For example, in [13], the authors report preventing customers from going through a specific activity multiple times. Several papers refer to actions toward resources, such as waiting for, involving more actively, increasing, replacing, reallocating, aggregating, manually inspecting, increasing the visibility of, protecting, or restricting access to a resource [11,23,58]. In [58], the authors observed that the pattern separation of duty should be applied to restrict access to certain parts of the information systems only to specific employees. In [11], the authors reported that the stakeholders are considering increasing the number of developers to resolve a ticket resolution time issue. Other papers refer to actions toward specific detected patterns in the process (either desired, i.e. good practice, or undesired), such as adopting or removing specific patterns [14], defining or improving good practices [6,64]. Other papers report on identifying or understanding specific patterns, or identifying the following –or possible exploitation– of good practices [27,47]. Although these papers reporting on identifying or understanding specific patterns or good practices could fit the intervention space "Analysis", we kept them under the "Process" intervention space because of the explicit relation to the intervention to the process.

4.5 Most Frequently Reported Insights and Actions

The most recurrent insights reported in the literature are related to:

1. *Low data quality*: Low data quality may refer to both the data from the databases as well as the event log itself. For example, in [54], the authors reported on missing fields in records and incorrect event sequences in the

event log. In [26], the authors reported on identifying incomplete traces. As such data quality issues may compromise the validity of the obtained insights, they need to be addressed before any further action can be taken.
2. *High wait time*: High wait time is a common concern in different contexts. For example, in [60], the authors noticed that it was taking more time for a process participant to take over a specific task than to work on that task. In [31], the authors report on identifying the delivery of goods taking longer than the defined service standard.
3. *High amount of rework*: Rework is another frequent concern. For example, the authors of [63] identified rework caused by manually misclassified documents. In [52], the authors identified that a specific system feature-related data had not been cached, requiring the user to unnecessarily repeat the execution of another related task within the system.
4. *Discovered process model*: The discovered process model is used for a variety of purposes. If, however, the discovered process model does not allow the analyst to obtain the required insights, this might be addressed before any further action can be taken. For example, the authors of [59] obtained spaghetti-like process models, which did not allow them to conduct a proper analysis of the process. In [19], the authors discussed the suitability of the discovered process model to support the definition of a standard process.
5. *Non-compliant behavior*: Besides performance-related insights, non-compliant behavior, i.e. conformance violations, represent a very common trigger for actions. For example, in [40], the authors identified actions performed by process participants that were not conforming to the expected behavior. In [62], the authors reported on an inward cargo handling where they identified many instances of the process that did not properly complete according to a normative process model.

Other insights refer to, for example, high or low demand on a specific resource (e.g., process participant), high execution time of specific activity, low automation rate, lack of domain knowledge, among others.

Figure 3 presents the top five most frequently reported insights and actions in the literature, respectively, in terms of the number of supporting quotes from the selected papers, as described in Sect. 3.3. For the reader to distinguish with ease the connections between insights and the process-related artefacts of the intervention space, we chose to repeat both action verbs and objects as triggered for each reportedly acquired process mining insight. Two aspects stand out from Fig. 3. First, the intervention space is quite large, highlighting that process mining insights not only trigger interventions to the process under investigation, but also to process-related artefacts. Second, there are many-to-many relations between acquired process mining insights and triggered actions, as well as between insights and process-related artefacts, objects of the intervention space. Have in mind that because there is a wider variety of actions than insights reported and the same amount of supporting quotes connecting insights and actions, the amount of supporting quotes for the most recurrent reported action is lower than for the most recurrent reported insight.

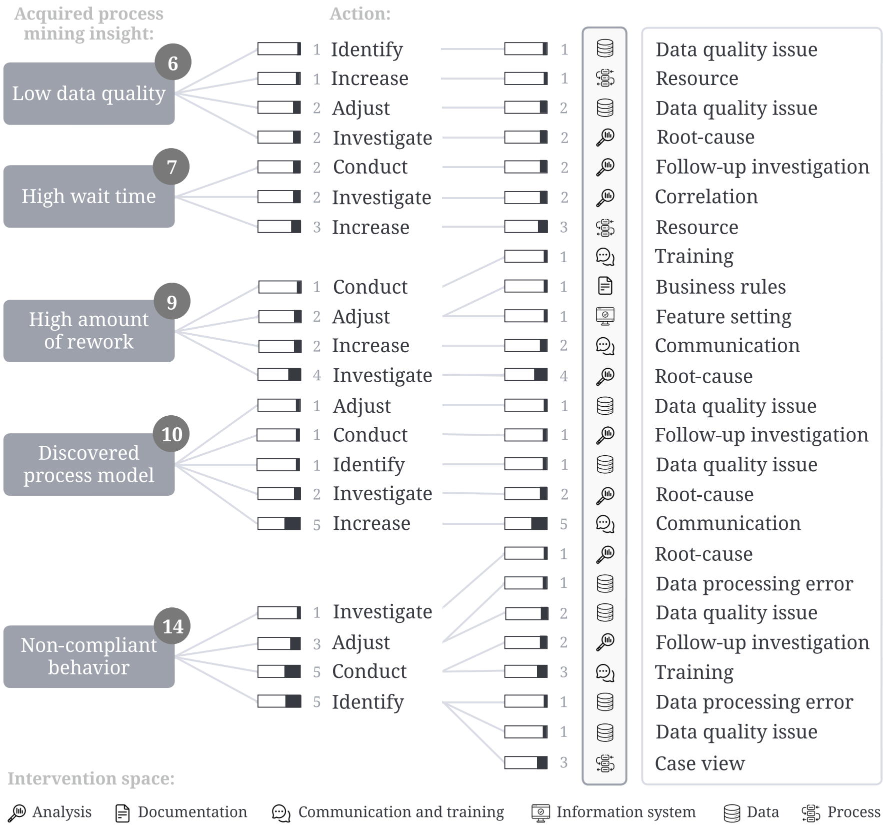

Fig. 3. Most frequently reported process mining insights and triggered actions.

5 Discussion

From our findings, it is clear that translating process mining insights into process improvement requires cooperation and coordination as different levels of knowledge and expertise are needed to support understanding and documenting the process, improving the involved information system supporting the investigated process, and improving the investigated process. We can reason that there is a need to properly operationalize the integration between technical and organizational workers to intervene in the process itself and in the underlying information system(s) while understanding and documenting the process, both coordinately and supported by domain and data knowledge.

While we do not claim to provide a comprehensive list of actions triggered by process mining insights, we provide an initial step toward understanding the diversity of the insight-to-action realm. We acknowledge that further research is needed to investigate the representativeness of the actions herein shown and a deeper understanding of each action, precisely detailing what they entail. Only then we'll be able to move towards ultimately recommending assertively follow-up actions from acquired process mining insights and triggering (semi-) automated actions not only related to prediction-based alert systems but also towards undertaking specific changes to the process or process-related artefacts.

Having this said, there are several important findings we were able to derive in this paper. Below, we discuss the three main points.

Actions are Concerned with Much More than the Process Itself. Intuitively, one would expect that process improvement is mostly about the process itself, especially when the basis for improvement are insights obtained through process mining. Our findings show that the investigated process is indeed subject to several actions, such as parallelizing or removing activities. We, however, could also show that there are several intervention spaces besides the process itself. Among others, we identified that actions are taken towards understanding or improving other process-related artefacts, such as documentation, communication, training, and supporting information systems. These findings highlight that process improvement requires a holistic view, including several facets, such as the IT infrastructure and the human resources that are involved in the process execution.

The Relationship Between Insights and Actions is Highly Complex. Our analysis revealed that there is a many-to-many relation between insights and actions. This means that one insight can trigger several actions and that one action can be triggered by several insights. While this is not totally unexpected, it helps to better understand the relationship between insights and actions. What is more, researchers and practitioners conducting a new process mining initiative can plan ahead for actions they may need to perform based on the insight they have obtained. In addition, they can also acquire a broader vision of potential insights to consider obtaining. Assume the actions they may need to perform are related to another insight that was not previously considered to be obtained. In this case, this not previously considered to be obtained insight could be added to the pool of insights to be acquired.

Gap Between Recommended and Taken Actions. During our analysis, we observed a gap between recommended and taken actions. For several insights, e.g., high wait time and high rework rate, we identified recommended but not any taken actions. This observation shows that certain actions seem to be either associated with too much effort or they are not considered for other reasons. While we cannot provide specific insights into why this gap exists, it is important to note that it is there. We believe that this represents an important direction for future work: understanding which actions are (not) performed to improve processes and why.

6 Conclusion

In this paper, we used a structured literature review to investigate which types of actions organizations have taken in the context of process mining initiatives and to which insights these actions are linked. We found that there exists a large variety of actions and that many of these actions do not only relate to changes to the investigated process but also to the associated information systems, the process documentation, the communication between staff members, and personnel training.

With these findings, our study provides an important step towards enhancing the implementation phase (as reported by Emamjome et al. [17]) of existing process mining methodologies. Specifically, the derived overview of actions triggered by process mining insights can serve as a catalog for practitioners that aim to translate process mining insights into actual process improvement. We believe that such a catalog can be particularly useful for novice process mining consultants and managers as it provides guidance on which actions they might consider given particular insights. Such catalog may also support practitioners sketching initial *plans of action* for their projects, supported by evidence from real-life case studies.

From an academic point of view, our results complement existing process mining methodologies, such as [1,9,15]. By including our findings, it is possible to devise a methodological framework for process mining that does not stop with obtaining insights but with realizing process improvements. Having this said, there are several aspects that require further investigation. First, it is interesting to conduct a deep investigation of what each action entails. For example, what are the different departments and personnel involved and what were the challenges faced while implementing a specific action. Second, it would be useful to conduct case studies with successful and unsuccessful process mining projects to highlight commonalities and differences between these projects and further understand which actions ultimately lead to a successful translation of process mining insights into process improvement.

In future work, we will conduct a survey with experts and a multiple case study to complement the intervention space taxonomy presented in this study. We will further investigate the relations between recommended and performed actions to move towards well-informed recommendations supported by performed actions. Finally, we will derive a catalog of the many-to-many relations between insights and the affected process or process-related artefacts.

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