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Analysis templates for identifying improvement opportunities with process mining

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ANALYSIS TEMPLATES FOR IDENTIFYING IMPROVEMENT OPPORTUNITIES WITH PROCESS MINING

Research Paper

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Abstract

Process mining tools help analysts in conducting a data-driven analysis of business processes. However, identifying improvement opportunities is still a manual task that depends largely on analysts' expertise and experience with process analysis and process mining tools. In this paper, we present a set of templates that aid analysts in systematically identifying improvement opportunities with Apromore. Based on review studies, we identified 22 improvement opportunities identifiable from process logs. Then, we conducted a content analysis of 129 business process intelligence challenge submissions to elicit how improvement opportunities can be identified. Based on this data, we developed 21 templates that guide process analysts in identifying improvement opportunities using Apromore. We evaluated the templates by conducting interviews and surveys with 12 participants to assess the templates' usefulness and ease of use. The evaluation indicates that the templates are useful (score 4.37/5) and easy to use (4.65/5) for identifying improvement opportunities with Apromore.

Keywords: Process analysis, Process mining, Analysis templates, Process improvement.

1 Introduction

To stay competitive, companies continuously improve their business processes (Dumas *et al.*, 2013). Business Process Management (BPM) is a body of methods, techniques, and tools to identify, discover, analyze, redesign, implement, and monitor business processes to optimize their performance (Dumas *et al.*, 2013). In the analysis phase, analysts identify weaknesses, i.e., improvement opportunities, in the business processes (Becker *et al.*, 2012). Thus, BPM is a continuous cycle where identifying improvement opportunities is a prerequisite for process change (Dumas *et al.*, 2013).

Business processes are often supported by information systems that log process execution data. Such *event logs* include sequences of timestamped events, each representing the execution of an activity. Process mining is a family of methods that enable data-driven BPM by using event logs to discover process models (Augusto *et al.*, 2019), enhance models (de Leoni, 2022), analyze performance (Milani and Maggi, 2018), predict (Di Francescomarino *et al.*, 2018), and prescribe case outcomes (Kubrak, Milani, Nolte, *et al.*, 2022). One common use case of process mining is process analysis, i.e., data-driven analysis of processes from different perspectives, such as batching (Lashkevich *et al.*, 2022) or waiting times (Dogan, 2022) for the explicit purpose of identifying improvement opportunities.

Methodologies, such as the PM^2 methodology (van Eck *et al.*, 2015), have been proposed to aid in applying process mining. However, PM^2 and similar methods are limited in their support for identifying improvement opportunities. Such methods focus on *what* rather than *how* to analyze business processes (Kubrak, Milani and Nolte, 2022). Therefore, analysts use process mining tools, but they manually identify improvement opportunities either applying high-level guidelines or based on their experience (Kubrak, Milani and Nolte, 2022). Currently there are no templates that can instruct analysts, especially those with limited experience in process mining, *how* to identify improvement opportunities when analyzing business processes with a process mining tool. This paper addresses this gap.

The objective of this paper is to develop and evaluate templates that process analysts can use to systematically identify improvement opportunities with process mining tools. To this end, we first seek to understand what improvement opportunities can be identified with process mining tools. Therefore, we address the research question (RQ1) of "*What improvement opportunities can be detected from event logs using process mining tools?*" Secondly, we examine how such opportunities can be identified (RQ2) by asking, "*How can improvement opportunities be detected from event logs using Apromore?*" However, as there are dozens of process mining tools, each with its own design ("Process Mining Tools 2020", n.d.), we use Apromore as a basis for developing the templates, primarily since a full version of the tool is available for academic purposes.

The contribution of this paper is a set of templates that provide step-by-step instructions for process analysts to identify improvement opportunities. These templates are designed so that process analysts with basic experience in process mining and Apromore can use them. In addressing the research questions, we conduct content analysis to develop templates. Finally, we evaluate the templates by conducting semi-structured interviews and a follow-up survey with 12 participants.

The remainder of this paper is structured as follows. Section 2 introduces the background and discusses related work. Section 3 presents the methodology followed by Section 4, which describes the results. Section 5 presents the evaluation results, and finally, we conclude the paper in Section 6.

2 Background and Related Work

Business process improvement typically begins by describing a business process as a model (Dumas *et al.*, 2013). The as-is process models are analyzed to identify weaknesses or segments that, if addressed, can improve process performance (Delfmann and Höhenberger, 2015). Analysts, therefore, use different tools and techniques, such as conducting information flow analysis, cost analysis, or root-cause analysis (CBOK, 2009) to identify how a process can be redesigned. However, many business process executions are supported by information systems that capture execution data such as timestamps, case identifiers, and executed activities (Dumas *et al.*, 2013).

Such data, a.k.a. event logs, are used by process mining techniques to, for instance, discover (Milani *et al.*, 2022) and analyze (Kubrak, Milani and Nolte, 2022) business processes. Process mining-based analysis often requires using process mining tools. There are open-source (e.g., ProM) and commercial tools available (e.g., Celonis and Disco), as well as those providing both commercial and academic licenses (e.g., Apromore) ("Process Mining Tools 2020", n.d.). Process mining tools are increasingly used by companies and process analysts (Wixom and Watson, 2010). For instance, BMW and SAP use process mining (Kerremans, 2019) to identify ways to improve process performance (Davenport and Spanyi, 2019). However, while process analysts are supported by process mining tools, the identification of improvement opportunities is conducted manually (Kubrak, Milani and Nolte, 2022).

Process mining has been used to improve business processes. For instance, Son et al. (2014) propose a framework for how process mining can be applied in industry. Their framework outlines four steps: data preparation, pre-processing, process mining & analysis, and evaluation & interpretation. Analysts identify improvement opportunities in the third step, and the framework proposes to conduct different types of analysis, such as bottleneck or resource performance analysis. Similarly, Gupta, Serebrenik, and Jalote (2017) propose a framework to identify improvement opportunities for ticket management of software maintenance processes. The identification of improvement opportunities is conducted in the last step with bottleneck, loop, conformance analysis, and social network analysis. Măruşter and van Beest (2009) propose combining process mining and simulation techniques. Their proposed approach consists of four steps: define the relevant performance criteria, mine the as-is process, simulate as-is and to-be processes, and compare as-is with the to-be. These works propose an end-to-end workflow for using process mining in industry and propose types of analysis, such as bottleneck analysis. However, they do not specify how analysts can identify such opportunities. Our work seeks to address this gap by providing templates that guide analysts in identifying specific improvement opportunities.

In Ganesha, Dhanush, and Raj S.M. (2017), the authors propose an algorithm that detects opportunities to reduce waiting time by optimizing resource usage in a healthcare process. Likewise, Awad, Zaki, and Di Francescomarino (2016) propose an automated approach to identify and resolve inefficiencies stemming from multi-tasking in a software development process. Similarly, (Lashkevich *et al.*, 2022) propose a semi-automated method for detecting batch processing inefficiencies. These studies rely on event logs to identify improvement opportunities in business processes. However, they focus on one improvement opportunity. We, on the other hand, consider multiple improvement opportunities.

3 Method

Our research objective is to develop a set of templates for identifying improvement opportunities when analyzing business processes using Apromore. In this section, we describe our approach to develop and evaluate the templates. Figure 1 presents the main steps of our approach. First, we collected and analyzed data to determine *what* improvement opportunities can be identified with process mining tools. To do so, we used the content study method to analyze studies focused on identifying improvement opportunities. Then, we determined *how* process analysts identify improvement opportunities with process mining tools. Following the content study, we elicited instructions for their identification from the BPI Challenge (BPIC) reports. Second, based on the collected data, we developed templates for Apromore. Finally, we evaluated the templates using a qualitative observational approach (semi-structured interviews and surveys). In this section, we elaborate on each step.

Steps	Data Collection and Analysis	Developing Templates	Evaluation
Inputs	Research gap.	• IOs that can be identified with the PM tool. • IO identification instructions.	21 analysis templates.
Activities	1. Formulate research questions. 2. Define data collection and analysis strategy. 3. Elicit improvement opportunities (IO) from 3 SLRs. 4. Elicit the IO identification instructions from 129 BPIC reports.	Develop templates.	1. Define evaluation protocol. 2. Conduct interviews and surveys. 3. Analyze interview and survey results. 4. Implement suggested template improvements.
Outputs	• IOs that can be identified with the PM tool. • IO identification instructions.	21 analysis templates.	Improved 21 analysis templates.

Figure 1. Research methodology.

3.1 Data Collection and Analysis

To develop analysis templates, we identify improvement opportunities that can be detected from event logs with process mining tools. Furthermore, we need to determine how such improvement opportunities can be detected from event logs with process mining tools. Therefore, we define our research questions as (RQ1) "*What improvement opportunities can be detected from event logs using process mining tools?" and (*RQ2) "*How can improvement opportunities be detected from event logs using Apromore?"*

To address the first research question, we identified papers that relate to identifying improvement opportunities. More specifically, we considered systematic literature review studies that discuss improvement opportunities in business processes. The first paper was Lashkevich (2020). The author conducted a systematic literature review of 150 papers and identified 101 improvement opportunities. The second paper was by Sharma (2021), which focused on identifying process wastes with process mining. In this study, the author reviewed 187 papers and identified 8 wastes detectable from event logs. Finally, we also included Reijers and Mansar (2005). This paper provides an overview of 29 redesign heuristics for process improvement derived from 11 papers. Collectively, these papers reviewed 348 papers and discussed 138 ways to improve business processes[1].

1 The total number includes duplicates, e.g., both Lashkevich (2020) and Sharma (2021) discuss overprocessing as an improvement opportunity.

We filtered the improvement opportunities by following two criteria. First, we excluded duplicate improvement opportunities. Secondly, we assessed if the improvement opportunity could be identified from event logs. For instance, the improvement opportunity “lack of experience” concerns situations where a resource lacks the skills or knowledge required for executing an activity (Lashkevich, 2020). However, event logs do not contain such information. Hence, it is not possible to identify the “lack of experience” with process mining tools, and, therefore, it is excluded. Having applied these criteria, we composed a list of 22 improvement opportunities detectable with process mining tools. We noticed that identifying improvement opportunities with process mining tools can be limited due to the unavailability of required data in the event logs, such as “lack of expertise” or “unavailability of input in time,” e.g., when a resource waits for raw materials delayed by the supplier (Lashkevich, 2020). In addition, when the data is available, process mining tools might lack support for identifying specific improvement opportunities, e.g., “insufficiently scheduled batching” (Lashkevich *et al.*, 2022). Therefore, identifying such improvement opportunities require additional input from process analyst. Complete list of reviewed improvement opportunities is available in supplementary materials[2].

To address the second research question, we analyzed relevant literature to elicit how improvement opportunities are identified with process mining techniques. For that, we conducted a content analysis. It allows deriving deeper insights from the investigated literature to get exhaustive input for developing templates (Mayring, 2020). Therefore, a qualitative research approach is suitable (Recker, 2012). We followed the guidelines for qualitative content analysis and (1) determined which materials to study, (2) then, based on the research question, defined categories and codes to iteratively annotate the materials, (3) reviewed and annotated the selected works, (4) frequently revising the formulated categories and codes, and, finally, (5) interpreted the results (Mayring, 2020).

We selected BPI Challenge (BPIC) submission reports. BPIC is an annual competition where students, academics, and industry professionals are given a real-life log to analyze and address a set of questions. We chose BPIC reports because, here, people with process mining expertise describe their analysis process and results. The contestants are free to use tools, methods, or techniques to analyze real-life logs. Although the reports do not explicitly focus on describing the improvement opportunity identification, they represent a broad collection of analysis descriptions presented in detail and validated by the reviewers. In addition, for each challenge, there are multiple submissions, which allows for comparing the approaches. Depending on the process and the challenge goal, the reports answer different questions, e.g., compliance-related questions, root-cause analysis, identifying issues. Therefore, we reviewed all available BPIC submission reports from 2011-2020 (129 reports). Although some reports might contain errors or inaccuracies, they were peer-reviewed. Therefore, we consider them reliable.

When analyzing the submission reports, we defined categories and codes following the guidelines of Mayring (2020). Thus, we derived categories and tags from the research questions. The first category included general information about the papers, such as *“submission ID,” “title,”* and *“author(s).”* The second category comprised improvement opportunities obtained from RQ1, e.g., *“bottleneck”* and *“rework.”* The third category included tags on how improvement opportunities were identified, e.g., *“event log attributes used to identify an improvement opportunity”* and *“feature of process mining tool used.”* In the fourth category, we tagged step-by-step descriptions of how each improvement opportunity was identified. Overall, we used 35 tags in 4 categories to analyze the studies.

After examining and tagging 10% of the reports, we revised and modified the tags. Having completed the tagging, we clustered the results based on improvement opportunities. Context-specific improvement opportunities, such as not user-friendly websites, were discarded. Similar improvement opportunities, such as waiting time due to internal resources and waiting time due to external input, were merged.

3.2 Developing Templates

Based on the input from our content analysis, we developed 21 templates for identifying improvement opportunities. The templates were designed specifically for Apromore, a commercial process mining

[2] bit.ly/42Rx2XP

tool. We chose Apromore as it is a commercial tool and, therefore, preferred by organizations over open-source solutions due to the reliability of performance and support. In addition, templates provide detailed step-by-step guidance and, therefore, must be tool specific as process mining tools differ in their design and feature support. Finally, unlike most commercial tools, a full version of Apromore is available for academic purposes, allowing us to use its full range of functionalities needed to develop templates.

The target audience for these templates is process analysts with limited process mining experience. Therefore, we designed the templates in sufficient detail to enable analysts to identify improvement opportunities they had not encountered before or identified with process mining tools. For instance, we included screenshots to aid in navigating and explained how to interpret the obtained outputs.

To develop the templates, we clustered the data extracted from the content analysis based on the improvement opportunity. Thus, for each improvement opportunity, we collected all descriptions of how it can be identified. Then, we analyzed the data and formulated the ways the opportunities can be identified with Apromore. Since reports differed in the level of detail and methods used, we translated (i.e., adapted) their descriptions into instructions in Apromore. We did not replicate the steps in the BPIC reports but adapted them according to the capabilities of Apromore. In addition, we used Apromore internal training materials as supporting means in developing templates.

3.3 Evaluation

To evaluate the templates, we conducted a qualitative observational study with participants familiar with process analysis using process mining. This method allows for an understanding of how participants interact with the templates to identify improvement opportunities (Lazar *et al.*, 2017). Since the templates are aimed at aiding analysts, we sought to understand the perception of the participants about the templates' usefulness and ease of use. Such aspects as usefulness and ease of use are latent variables, i.e., variables that refer to the personal experience of the user and, thus, cannot be directly observed and measured. To evaluate such variables, the users are typically asked sets of questions that *collectively* determine, e.g., how useful or easy to use an artifact is (Mertens *et al.*, 2017). Therefore, we based our evaluation on the Technology Acceptance Model, a.k.a. TAM (Mertens *et al.*, 2017). According to TAM, users intend to use templates when perceiving them as useful and easy to use. Therefore, TAM describes the relationship between perceived usefulness, perceived ease of use, and intention to use (Mertens *et al.*, 2017). Accordingly, we formulated three evaluation goals: assessment of usefulness (EG1), assessment of understandability (ease of use) (EG2), and identifying possible improvements of the templates (EG3). We excluded "intention of use" to eliminate biased results, as some of the participants were students with no explicit intention of using the templates. The evaluation comprised a semi-structured observational interview and a follow-up survey. A similar evaluation strategy has been used to e.g., evaluate explanation plots in the predictive process monitoring (Rizzi *et al.*, 2022).

We recruited 12 participants and divided them into two groups based on their level of experience with BPM and Apromore (Table 1). The first group consisted of 6 participants with basic to moderate knowledge of BPM and Apromore, i.e., less than one year of experience. These were, for instance, university students who had completed BPM and process mining courses and used Apromore for their assignments. This group matched the target audience of the templates. The second group consisted of 6 participants with more than 1 year of experience with BPM and Apromore. These participants work with BPM and process mining as part of their profession, such as process analysts and researchers. Although this group is not necessarily the target audience of the templates, involving experienced analysts allowed for validating the selected templates' content, getting improvement suggestions, and additional insights on their potential applicability in the field. The number of participants (12) was determined based on data saturation, i.e., when no significantly new information was obtained (Fusch and Ness, 2015).

Participant ID	I01	I02	I03	I04	I05	I06	I07	I08	I09	I10	I11	I12
Years of Experience	0,5	0,5	3	0,5	5,5	0,5	3	1	1,5	3	2	0,8
Group	1	1	2	1	2	1	2	2	1	2	2	1

Table 1. Participants (Group 1 - basic to moderate, Group 2 - advanced experience).

During the interview, participants were asked to use selected templates. We observed them using the templates and asked a set of questions. We opted for semi-structured interviews since they allow open conversation and, thus, promote the emergence of new topics while still providing sufficient structure for the discussion (Edwards and Holland, 2013).

In total, we evaluated 9 templates. We did not evaluate all 21 templates because (1) the aim was to evaluate the overall usefulness and understandability of the templates, not each one, (2) evaluating all templates would require more time and would be inefficient considering the capacity and focus of the participants, and (3) as information is perceived differently by different participants, we prioritized evaluating the same template several times in both groups. Given this constraint, the templates were clustered based on similarity. For instance, templates for identifying small activities and large activities are similar. Following this principle, we organized the 21 templates into nine groups. For the evaluation, we selected one template from each group. We used two different event logs (loan origination and refund processes) since we could not find one event log that included all improvement opportunities.

After the discussion, the participants filled out a survey based on TAM. It consisted of three sections: perceived usefulness (PU), perceived ease of use (PEOU), and demographic questions. Questions on PU considered the usefulness of the templates when identifying improvement opportunities, defining the required data, enhancing effectiveness, identifying relevant redesign options, and the overall usefulness of the templates. For PEOU, we asked questions concerning the clarity and understandability of the templates, learning to use the templates, and ease of use. We used a scale ranging from 1 (strongly disagree) to 5 (strongly agree) for these questions. The demographic section captured data on gender, age, years of experience, and process mining tools participants have used. We used the survey to evaluate EG1 (usefulness) and EG2 (ease of use).

The interviews were conducted online except for one (I03), which was conducted in person. Each interview took about an hour and was recorded. The recordings were transcribed and analyzed using affinity diagrams (Plain, 2007). The affinity diagram method is suitable as it allows for collaborative analysis of unstructured data, e.g., interviews (Lucero, 2015). The transcripts were coded in an iterative way: we started with a preliminary set of codes formulated based on the evaluation goals (e.g., "useful" and "not useful"), then we revised and, if necessary, updated the codes after every analyzed interview. In the end, 21 codes, such as "definition," "examples," "guidelines," "incompleteness of information," "structure," "issues," and "content improvement," were elicited. These were categorized into five themes (content, usefulness, understandability, ease of use, and improvement) and connected to the evaluation goals. The themes "content" and "usefulness" relate to EG1, "understandability" and "ease of use" to EG2, and "improvement" to EG3.

Following the coding, we analyzed the results to derive findings. We also listed the suggestions for improving the templates. We prioritized the suggestions according to "must," "should," "could," and "won't." We prioritized suggestions that were mentioned by more than one person, required low effort to implement, and/or will add high value as a "must." Suggestions mentioned by only one person, requiring medium-level effort, and with limited value were prioritized as "should." Finally, suggestions requiring high effort or out of scope were marked as "could" and "won't." We implemented all "must" and "should" suggestions. The evaluation study protocol is available in supplementary materials.

4 Results

In this section, we present the results. We first describe improvement opportunities that can be identified with process mining tools (RQ1). Then, we consider how such improvement opportunities can be detected with process mining tools (RQ2). Finally, we present the structural outline of the templates by using the example of the template for identifying bottlenecks.

4.1 Identifying Improvement Opportunities with Process Mining

We identified 22 improvement opportunities detectable with manual analysis of event logs with process mining tools. Moreover, we grouped them into 7 categories based on similarity (see Table 2). The first category consists of improvement opportunities identified by examining attributes of specific activities.

For instance, identifying small (short processing time) (Dumas *et al.*, 2013) or large activities (long processing time) (Souza *et al.*, 2017) presents an opportunity for improvement (Lashkevich, 2020). Likewise, if an activity exhibits abnormal variations in processing time, there is a potential for improvement (Thabet *et al.*, 2018). Thus, we group them as "activity specific."

Two of the improvement opportunities are related to resource utilization. If the resource utilization is low (Lohrmann and Reichert, 2016) or high (i.e., the ratio between resource occupation and availability is low or high respectively) (Al Badi, 2019), there is an opportunity for improvement (Lashkevich, 2020). We group these two as "resource specific."

A set of improvement opportunities relate to both activity and resource. For instance, "frequent handovers," i.e., when a case is frequently transferred between resources in the process (Cho *et al.*, 2017), is an improvement opportunity. Likewise, when a case is transferred back and forth between resources to execute sequential activities, i.e., the "ping-pong behavior" (Delias, 2017), it is also an opportunity for improvement. We group such examples as "activity-resource specific."

Improvement opportunities such as rework (Dumas *et al.*, 2013) and knock-out checks (Verenich *et al.*, 2016) concern control flow, i.e., the ordering of the execution of activities. Rework is the repeated execution of tasks in the same case due to, for instance, a defect. Knock-out, on the other hand, is when cases are rejected later than necessary and, thereby, incur overprocessing of a case (Verenich *et al.*, 2016). We group these as "control flow specific."

Unnecessary waiting times in business processes are viewed as an improvement opportunity (Dumas *et al.*, 2013). For instance, by examining event logs, analysts can identify the highest waiting times in a process (Mans *et al.*, 2008), cases with the highest waiting times (Rojas *et al.*, 2019), and bottlenecks (Li *et al.*, 2009). In addition, high processing times can also slow down the whole process, e.g., due to manual and time-consuming process fragments (Yao *et al.*, 2017). When high waiting and processing times are detected, there is a potential for improvement. Thus, we group these as "time specific."

Overprocessing, i.e., steps that are unnecessarily performed in a process, is considered a waste (Thürer *et al.*, 2017). Similarly, overproduction, i.e., the production of output that is not needed, is also considered a waste (Thürer *et al.*, 2017). We group them as "waste-specific."

Finally, manually executed processes (Shraideh *et al.*, 2009), processes with a high degree of complexity (Frank *et al.*, 2020), and similar variants (Bergh *et al.*, 2013) are also candidates for improvement. These improvement opportunities consider the whole process and, as such, were grouped as "process specific."

Category	**Improvement opportunity**	**Definition**
Activity specific	Small activities	Activities with few procedures and short processing time.
	Large activities	Activities with many procedures and long processing time.
	Activity variants	Activities with abnormal variation in performance.
	Similar activities	Non-identical activities with common attributes and similar procedures.
Resource specific	High resource utilization	High ratio between occupation and availability of resources, i.e., resources are often too busy.
	Low resource utilization	Low ratio between occupation and availability of resources, i.e., resources are rarely occupied.
Activity-resource specific	Internal checks	Activities where internal human resources perform checks.
	Independent sequential activities	Activities executed sequentially but not dependent on each other in terms of inputs, outputs, and resources.
	Frequent handovers	Frequent transferring of the case from one resource to another for checks, controls, decision-making, or further processing.
	Ping-pong behavior	The case, transferred from one resource to another between two consecutive activities, is returned to the previous activity.
Control flow specific	Rework	Repeated execution of activities for the same case.
	Knock-out checks	Activities that classify cases as accepted or rejected, such that if rejected, the effort spent on this case is redundant.
	Workarounds	Process paths that deviate from standard process execution but reduce known issues or help achieve an unsupported objective.

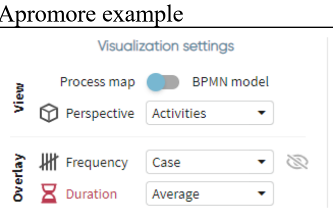
Time specific	Highest waiting time in the business process	The longest average time that cases spend in an idle mode (waiting for further processing) between two activities.
	Cases with the highest waiting times	Cases with the highest total time in an idle mode (waiting for further processing).
	Bottlenecks	The arrival of the cases exceeds the number of cases that can be processed, resulting in a build-up of cases and long waiting times.
	Manual time-consuming fragments	Fragments where all or most activities are executed manually and have a long throughput time.
Waste specific	Overprocessing	Activities executed unnecessarily given the outcome.
	Overproduction	Executed process instance, the output of which is not required.
Process specific	Manual process	Process, where all or most activities are executed manually.
	High complexity	Process with a high number of decision points, loops, and branches.
	Similar variants	Process, where several process variants are similar in how they execute cases for different products, customers, or in different locations.

Table 2. Improvement opportunities detectable from the event logs with process mining tools.

4.2 Analysis Templates

Based on the 22 identified improvement opportunities from RQ1, we developed 21 analysis templates. We created one template for low and high human resource utilization as their only difference lies in interpreting the results, i.e., identifying resource utilization ratio and, based on the obtained values, interpreting if the resources are under- or over-utilized.

All templates follow the same structure. Each template begins with the name of the improvement opportunity followed by the definition. Then, we provide examples, i.e., short scenarios that illustrate the improvement opportunity. We include these parts to aid analysts in understanding the improvement opportunities before identifying them. Then, we define the data required for identifying the improvement opportunity from the event log. Some improvement opportunities require additional data. For instance, waiting time-related improvement opportunities require both start and end timestamps for each activity. If one is lacking, it is not possible to identify improvement opportunities related to waiting times. As such, analysts can determine which improvement opportunities (templates) are applicable.

<table>
<tr><td>IO</td><td colspan="4">Bottleneck</td></tr>
<tr><td>Definition</td><td colspan="4">The arrival of the cases exceeds the number of cases that can be processed, resulting in case build-up and long waiting times.</td></tr>
<tr><td>Examples</td><td colspan="4">In the hospital, patients need to wait to make the computed tomography scan due to the lack of personnel, which causes queues.
In the pharmacy, customers need to wait in the queue to get served because pharmacists are busy serving other customers.</td></tr>
<tr><td>Minimum data needed</td><td colspan="4">Activities, start timestamps, end timestamps, resources.</td></tr>
<tr><td rowspan="2">Guidelines on how to identify this IO</td><td>#</td><td>Step</td><td>Apromore example</td><td>Explanation</td></tr>
<tr><td>1</td><td>• Open an event log in the process discoverer.
• In the Visualization settings, select Duration overlay and choose Average. In the View section, choose the Activities perspective.</td><td>
</td><td>The bottleneck is identified based on the long time needed to process the case or the long waiting time between activities.
Result of the step: generated process map based on the activity perspective and average duration.</td></tr>
</table>

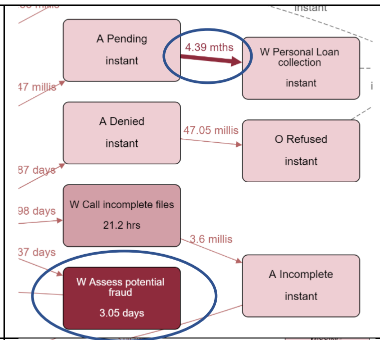
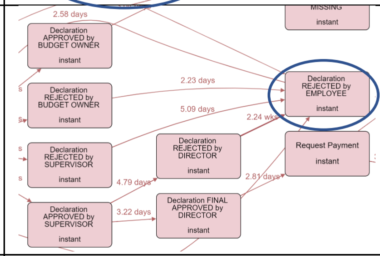
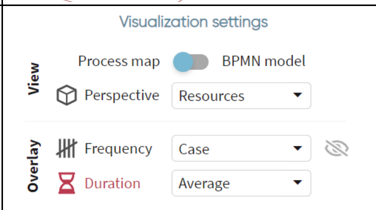
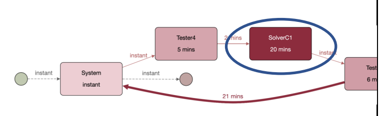
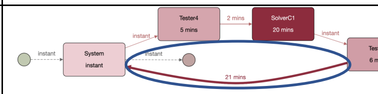
<table>
<tr><td></td><td>2</td><td>From the process map:
• Find activity bottlenecks: activities with the longest processing time. List these activities.
• Find waiting time bottlenecks: arcs with the longest duration. List activity pairs.</td><td>
</td><td>To find activity bottlenecks, define activities with the longest duration.
To find waiting time bottlenecks, find the longest waiting times (the thicker the arrow between activities, the higher the waiting time is). In the example, they are circled in blue.</td></tr>
<tr><td></td><td></td><td>• Find resource-capacity bottlenecks: activities with the highest number of incoming arcs with long arc duration. List these activities.</td><td>
</td><td>To find resource-capacity bottlenecks, define activities, all/most incoming arcs of which have long waiting times.
In the example, it is circled in blue.
Result of the step: list of activity, waiting time, and resource-capacity bottlenecks.</td></tr>
<tr><td></td><td>3</td><td>In the Visualization settings, select Duration overlay and choose Average. In the View section, choose the Resources perspective.</td><td>
</td><td>Result of the step: generated process map based on the resource perspective and average duration.</td></tr>
<tr><td></td><td>4</td><td>From the process map,
• Find resource bottlenecks: resources with the highest processing time from the resource perspective. List these resources.</td><td>
</td><td>To find resource bottlenecks, define resources with the longest duration. In the example, it is circled in blue.</td></tr>
<tr><td></td><td></td><td>• Find waiting time bottlenecks from the resource perspective: arcs with the longest duration. List these pairs of resources.</td><td>
</td><td>To find waiting time bottlenecks from the resource perspective, find the longest waiting times (the thicker the arrow between resources, the higher the waiting time is). In the example, it is circled in blue.
Result of the step: list of resource bottlenecks and waiting time bottlenecks from the resource perspective.</td></tr>
<tr><td></td><td colspan="4">Output: Activity and resource bottlenecks.</td></tr>
<tr><td>Redesign options</td><td colspan="4">• Implement a technological solution to minimize constraints in the process.
• Organize separate process paths for different types of orders.
• Add more resources to the business process if bottlenecks are caused by a lack of resources.
• Implement a scheduling system for clients to evenly distribute the workload if bottlenecks are caused by queues during peak hours.
• Implement a resource scheduling system that will allow having more resources during peak hours and fewer resources during periods with low demand.
• Introduce a buffer queue.
• Use incentives to shift customers from high-demand hours to low-demand hours.
• Allow customers to execute some parts of the process by themselves.</td></tr>
<tr><td>References</td><td colspan="4">BPIC: (Adriansyah and Buijs, 2013), (Brils et al., 2018), (Pakileva et al., 2020)
Academic papers: (Premchaiswadi and Porouhan, 2015), (Caballero-Hernandez et al., 2018)</td></tr>
</table>

Table 3. Analysis template for identifying bottlenecks.

Next, we describe how to identify the improvement opportunity. This includes a detailed description of each step and screenshots. This part also includes explanations of what to look for and the output of each step. We do not provide the reasons why there is such an opportunity. As the reasons are domain-specific, the analyst will have to investigate them separately. Then, we present possible redesign options that, if applicable and applied, could improve the business process. Finally, we added references to academic papers and BPIC submissions to provide additional resources and examples.

Table 3 presents the template for identifying bottlenecks. Following the described structure, the template starts with the name of the improvement opportunity (*bottleneck*) and its definition (*"the arrival of the cases exceeds the number of cases that can be processed, resulting in case build-up and long waiting times"*). Then, two examples from healthcare and pharmacy processes are provided, e.g., *when patients need to wait in long queues due to the lack of personnel*. To identify bottlenecks, analysts need an event log that at least includes activities, resources, start and end timestamps (see the *Minimum data needed* in Table 3). With this information, analysts can see if their event log has the required data to identify bottlenecks. The next section (*Guideline on how to identify this IO*) describes a step-by-step approach for identifying bottlenecks, including a description of actions to perform, a screenshot example of the results, and an explanation of how to interpret the results. In addition, the expected output is specified. For instance, in the bottleneck template, the expected output is *"Activity bottlenecks are found using Steps 1-2, resource bottlenecks are found using Steps 3-4"*. If an analyst's task is to only identify resource bottlenecks, they learn that they can proceed to Steps 3-4. The guideline also specifies the outcome of having completed all steps, e.g., a *"list of bottlenecks based on activities and resources."* Next, the templates elaborate on the potential redesigns that can address bottlenecks, such as *"add more resources to the business process if bottlenecks are caused by a lack of resources"* and *"implement a scheduling system for clients to evenly distribute the workload*." The last section provides references to publications that apply and discuss this improvement opportunity. The collection of 21 analysis templates is available in supplementary materials.

5 Evaluation

In this section, we present the results of our interviews, followed by the results of the survey. Finally, we discuss the limitations of our study.

5.1 Interview Findings

First, we evaluated the usefulness of the templates (EG1). The participants worked mainly with the guideline section of the templates, and most participants considered this section to be useful (I02, I03, I04, I05, I06, I08, I09, I10, I11). For instance, one participant said that "*this step-by-step guideline is very useful. Especially, I can imagine that it is very useful for novice users*" (I11). Another expressed that "*overall it's a good instruction*" (I01). Participants commonly commented on the usefulness of specific parts of the guideline section. For instance, one shared that "*the images are a good help because only with text it is more difficult to visualize it and understand it*" (I05). Other parts, such as the minimum data needed (I01, I06, I10), definition (I02, I11), improvement opportunity category (I02), and references (I06), were also generally considered useful.

Regarding the usefulness of minimum required data, one participant noted that it "*is also a good thing. Because when you have the data that needs to be there, the user can actually see that this is the minimum data that we require for this thing*" (I06). However, another participant expressed that "*I don't imagine yet how I could use it [minimum data needed]. Perhaps if I were to upload the event log first, it would help me, but I don't know about that yet because I haven't used it*" (I11).

Regarding definition, one interviewee said: "*The short definition of the improvement opportunity that we're looking at [is useful] because the name can be not very self-explanatory, so this helps*" (I11) and "*provides value to the end users*" (I02). Similarly, the reference section is considered "*a good thing. So, if somebody is doing the research project, they can actually refer to what exactly, they can use these references specifically*" (I06). At the same time, one participant considers the reference part useful for "academic work" because "*references are awesome, great, everyone loves them*" (I10). However, "*if you're going to put it into a company, maybe 10% actually care*" (I10).

A similar pattern was discerned for the examples. One interviewee expressed that "*I really like the example […]. So, it was pretty nice to understand the overall if the process can be a generic one, but you can actually read through the example to get to know that. So, this is an example, it does make a lot more sense*" (I06). However, another participant noted that "*I wasn't paying much attention to the example. […] I think the example is useful. It depends also on the experience of the analyst*" (I05). It seems that more experienced users, such as I05, find it less useful to have explanatory sections. At the same time, less experienced participants, such as I01 and I04, see greater usefulness for these parts. Finally, we note that participants did not mention the redesign section as either useful or not useful.

We also sought to evaluate the ease of use of the templates (EG2) by considering how understandable and easy to use they are. Understandability refers to how clear the content and structure are and the issues with understanding them. Overall, participants found the content to be clear and understandable. For instance, one participant expressed that "*overall, I liked the templates, and they seem very easy and clearly written, so it should be a great support and help for people who are especially new to different process mining tools*" (I09). The understandability seems to be high for all components of the templates. As one interviewee expressed, "*the improvement opportunity, the definition, the minimum data needed, I think all clear*" (I07). The structure of the templates was also generally considered understandable. One interviewee shared that "*what I especially loved about it is the structure of the template. That I know how they go, I know what I should expect, and I know what kind of steps I should perform and click what buttons. So, I would say that the structure is the strongest part of these templates*" (I09).

Some participants mentioned several issues with understandability. The comments suggested improving the explanations in the templates. For instance, one participant saw the need to "*add more human explanation of what they actually see on the screen*" (I01). Another was concerned about the use of the example event log. The respondent said that "*here in the insurance claims handling process activity assess claim is a large activity. I worked with these event logs before, so I know what insurance claims are and what is assess claims. But if I were to look at it first, I am not sure that it would be very self-explanatory to me*" (I11). One participant commented on the redesign part and expressed that they would benefit from an explanation of how the suggested redesign options are applicable to the improvement opportunity: "*I would say that sometimes the redesign possibilities seemed not so connected*" (I12).

A few comments were template specific. One participant shared two comments regarding the "High/Low Resource Utilization" template, expressing that "*how do I know if [Resource] 25 is still the lowest? It has 11 [cases], but it has much more than [Resource] 29. It is still like light blue"* and *"So, the first view [Step 1] was like how many times the resource does the task, and this one [Step 3] is how much time it takes to do it? ... I would really appreciate if it was written somewhere*" (I01). A similar comment was made for the "Activity variants." The respondent said that "*I was confused with the text, how it's written in the step. Because it says that I need to analyze both obtained distributions and I need to check for outliers, and then list this activity, and I was confused because here, what we're looking for is a graph which shows the average processing time for cases, and then somehow, I completely forgot that I already made here a filter for this particular activity and this just didn't work*" (I11).

Regarding ease of use, the participants generally found the templates to be easy to use. For instance, one participant expressed that "*from finding problems [improvement opportunities], I think it does the job really well. It really takes my hand and shows me exactly what I have to do and what I have to find*" (I12). However, issues such as "*too small screenshots"* (I01), "*need to detect improvement opportunities based on filtering some data, not just visually*" (I04), and "*confusing explanation of the guidelines section, where explanations are in the same column as the result*" (I12) limited ease of use.

The third evaluation goal concerned improving the templates (EG3) in terms of understandability and ease of use. Six participants (I01, I02, I04, I07, I10, I11) suggested adding an introductory section to the collection of templates explaining the aim of the document and how it is to be used, e.g., "*having some kind of introduction or preface. What are the templates about? And how do you use them?*" (I10). Three participants (I10, I11, I12) proposed improvements related to the categorization of the templates. For instance, one commented to "*maybe organize or group some of them [templates in the table of contents] together. One way to do it would be based on the minimum data needed*" (I10).

Two participants (I01, I07) suggested improving clarity by removing the expected output section, e.g., "*minimize the text of expected output. Just put the table with the step, examples and the explanation, that's it*" (I07). Another comment was about clarifying how patterns cause process inefficiencies. One participant commented that they are "*missing the part that tells me if I have those similar activities [for example], what is kind of the default danger. Why should I think that having similar activities is something that makes my process unoptimized?*" (I10).

Other suggestions concerned elaborating the examples "*so that you get a better idea before even going forward in these steps*" (I05). Another participant suggested introducing one simple process scenario and using it for all templates: a "*generic process which is known to everybody like going shopping for bread*" (I11). Furthermore, some suggested improving the images as "*they are pretty small here*" (I01) and including images for the redesign part because "*if you're telling me here a redesign possibility if you could somehow also show me how that should look like visually speaking*" (I12). We also received some minor recommendations such as "*add the hyperlink to the resources*" (I09) and "*instead of the reference to a particular paper, what would be useful specifically for me is rather a reference to a place where this improvement opportunities may be described in more detail but not in the entire paper*" (I11).

We prioritized the suggestions based on the number of participants who mentioned them, the value to the end user, and the required effort for implementation. We prioritized all suggestions as either "must," "should," "could," or "won't." In the end, we implemented 12 out of 29 suggestions (all "must" and "should"). The current version of the templates includes these improvements. Details about the suggestions and their prioritization are available in the supplementary materials.

5.2 Survey Findings

Here, we summarize the results for group 1 (participants with basic to moderate knowledge of BPM and Apromore) and group 2 (participants with advanced knowledge of BPM and Apromore). The survey consisted of 8 questions focusing on perceived usefulness and 5 questions on perceived ease of use.

The survey results show that both groups were mainly satisfied with the usefulness (EG1) and ease of use (EG2) of the templates. Group 1 rated usefulness 4,44, whereas group 2 rated it 4,29. For ease of use, group 1 rated it 4,63, and Group 2 rated it 4,67. Thus, both groups perceived the template as generally useful and easy to use. For perceived usefulness, Group 1 rated PU3 (*"Using templates would enable me to define what data I need to identify improvement opportunities more quickly"),* PU5 *("Using Templates would enhance my effectiveness in identifying improvement opportunities"*), and PU8 *("I would find templates overall useful"*) the highest (4,67) (see Supplementary materials). Group 2 rated PU5 and PU8 the highest with 4,83. These results seem to indicate the usefulness of the templates for identifying improvement opportunities.

Group 1 rated PU6 (*"Using templates would enhance my effectiveness in identifying relevant redesign possibility for each improvement opportunity")* the lowest with a mean grade of 4,0. This might be because we did not explicitly ask participants to interact with the redesign part. Group 2, on the other hand, rated PU2 (*"Using templates would make it easier to understand the meaning of improvement opportunities"*) the lowest (3,67). Group 2 participants are more familiar with BPM and, therefore, they might have relied less on the definitions to understand the improvement opportunities.

For ease of use, Group 1 scored PEOU3 (*"Structure of templates is clear and understandable"*) the highest (4,83). Group 2 rated PEOU4 (*"It would be easy for me to become skillful at using templates"*) the highest with 5,0. The lowest rating was given to PEOU1 (*"Learning how to use Templates would be easy for me"*) and PEOU2 (*"I would find it easy to use templates to identify improvement opportunities and redesigns"*). Both were rated 4,5 by Group 1. In Group 2, the lowest rating was given to PEOU2 (4,33). It seems that participants of both groups experienced some difficulties with ease of use. At the same time, it should be noted that the lowest ratings are still above 4.

The survey results did not show any significant variation between the two groups. Both groups gave high ratings for perceived usefulness and ease of use. As such, the results seem to indicate that the templates are useful and easy to use when identifying improvement opportunities with Apromore.

5.3 Limitations

Our study has limitations concerning examined papers, content analysis, applicability, and evaluation of the templates. The listing of improvement opportunities was based on three review studies. As such, there might be studies that were excluded from this research. However, this limitation is to some extent mitigated as these papers collectively examined 348 papers. Regarding the content analysis, the results are based on BPIC submissions. However, there might be approaches for identifying improvement opportunities not covered by BPIC reports. However, we included 129 submissions extending over ten years as a measure to reduce this risk. Another threat to validity is the bias of data extraction during the content analysis. We reduced this threat by frequently and iteratively revising the categories and tags, therefore, ensuring their refinement and reliability (Mayring, 2020). In addition, content analysis has an inherent limitation regarding the misinterpretation of results and incorrect generalization of patterns (Bengtsson, 2016). We mitigated this threat through regular meetings to discuss results.

The templates are designed for Apromore, and thus, their application is limited to Apromore. Further research could extend their applicability to other process mining tools. However, there is a potential challenge of reaching a balance between generalizability and a sufficient level of detail in providing instructions on how improvement opportunities can be identified, as each tool has its specific design.

Finally, we acknowledge the limitations of our evaluation. Our aim was to measure the perceived usefulness, ease of use, and understandability of the templates. However, we evaluated 9 of 21 templates to ensure that one template was used by several participants. This might mean templates not included in the evaluation are not as useful, easy to use, or understandable as the selected ones. In addition, the coding of interview transcripts was conducted by one author of this paper. This could cause interpreter bias. We mitigated these limitations by frequently discussing the findings.

Finally, we recognize that merely following the templates might not result in identifying improvement opportunities. In addition, it is possible that the user misinterprets the results. We attempted to mitigate this scenario by providing explanations of the expected outputs and how they can be interpreted. However, the potential bias of misinterpretation of the results remains and, thus, is a limitation.

6 Conclusion

In this paper, we examined which improvement opportunities (RQ1) and how analysts can detect them with process mining tools (RQ2). We identified 22 improvement opportunities that can be grouped as activity-, resource-, activity-resource-, control-flow, time-, waste-, and process-specific improvement opportunities. We also developed 21 templates that guide analysts in identifying improvement opportunities with Apromore. We evaluated the templates' usefulness and ease of use by conducting six interviews with users having basic to moderate knowledge of BPM and Apromore (G1) and six users with advanced knowledge (G2). Overall, the templates were perceived as useful by both groups (4,44/5 by G1 and 4,29 by G2). Similarly, ease of use was rated 4,63 (G1) and 4,67 (G2). Although the templates seem to be slightly more useful for novice users, advanced users also consider them useful. In addition, both groups consider the templates to be easy to use. As such, the templates can provide analysts with support when analyzing processes with Apromore. The templates focus on identifying improvement opportunities. However, process mining tools can be used to conduct other analyses, such as conformance checking. As an extension to this work, we aim to develop templates for other use cases.

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