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Towards Data-Driven Business Process Redesign Through the Lens of Process Mining Case Studies

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Abstract. Process mining is widely used for business process analysis, but rarely informs Business Process Redesign (BPR) activities. We review process mining literature and BPR framework to create thematic maps of state-of-the-art process mining analyses, techniques, outcomes and BPR best practices. We collect 156 case studies where process mining is applied and use them to validate the proposed themes. We reveal connections between the themes to explore the synergy between process mining and process redesign. Our work contributes to the development of an approach for BPR practitioners to systematically leverage the process mining capabilities, providing a solid starting point for data-driven BPR.

Keywords: Business Process Redesign · Business Process Redesign Best Practice · Process Mining · Case Study

1 Introduction

Business Process Redesign (BPR) is considered the most value-adding phase in the BPM lifecycle [10]. Reijers and Liman Mansar [31] propose a BPR framework encompassing 29 process redesign best practices to guide practitioners on their business process improvement initiatives. While this framework has been widely used across different industries, it is often difficult to replicate successful BPR projects, since most process improvement recommendations are relying on the practitioners' experience and expertise [15]. Process mining has proven its powerful capability in supporting process analytics [18], whereas process mining outcomes are rarely used to inform BPR activities [3, 29]. This has motivated us to explore the synergy between process mining and process redesign.

In this paper, we aim to address the open research gap about the disconnection between process mining and BPR activities, more specifically, how process mining can be used to inform process improvement recommendations. We propose a research design based on Nickerson *et al.* [28]'s methodology to guide our study from both a theoretical aspect and a practical aspect. We review process mining literature and BPR framework to create thematic maps of state-of-the-art process mining analyses, techniques, outcomes and BPR best practices by employing deductive thematic analysis method. We collect 153 case studies where process mining is applied and use them to validate the proposed themes. We investigate relationships between these themes to explore the synergy between process mining and process redesign.

Our work contributes towards the development of an approach for BPR practitioners to systematically leverage process mining capabilities and reduce the reliance on the practitioners' experience and expertise. As such, it provides a solid starting point for data-driven BPR.

2 Related Work

We present a few highly relevant research efforts that attempt to address data-driven process redesign. Cho *et al.* [7] develop a framework to assess the impact of a BPR best practice on process performance. The framework supports an evidence-based evaluation of BPR best practices using (process execution) event logs instead of second-hand data collected by interviews or questionnaires. The work focuses on evaluating the impact of BPR best practices rather than bridging the gap between process mining capabilities and BPR activities. Gross *et al.* [18] propose a preliminary framework to match BPR best practices and process problems that can be identified by process mining. The BPR best practices and process problems are matched subject to a two-round discussion among the authors. Systematic matching criteria for connecting process problems and BPR best practices are yet to be developed. Park and van der Aalst [29] propose an action-oriented process mining framework with an aim to connect the process mining insights and process improvement actions. The framework is designed to support process monitoring, detect violations and recommend actions to resolve the violations or mitigate their effects. The informed process improvement actions are rather specific and not guided by BPR best practices. Also, potential process deficiencies that do not trigger a violation might be overlooked.

3 Research Methodology

We adopt Nickerson *et al.* [28]'s research methodology to guide our study from a theoretical aspect and a practical aspect. Fig. 1 depicts our research design.

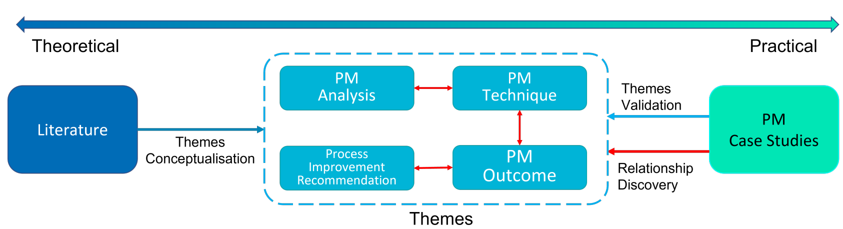

Fig. 1. A graphical overview of our research design

Conceptualise Themes We apply thematic analysis [4] to conceptualise process mining and BPR-related topics into four themes: **process mining analysis** for activities that utilise process mining capabilities to address analytical questions [12]; **process mining technique** for techniques specifically developed for process mining analysis activities; **process mining outcome** for outputs (such as insight [3], finding [19], result [9]) produced by deploying process mining techniques; and **process improvement recommendation** for recommendations or countermeasures to improve process performance and/or compliance.

We employ purposive sampling as our literature search strategy. We search for papers that apply systematic approaches, such as systematic literature review and systematic mapping, using search string " 'process mining' AND systematic". Our study excludes papers that are not domain/industry-independent. We also search for papers that discuss a process mining technique specifically. We add keywords informed by the process mining use cases from [24] to our initial search string. The BPR framework and best practices are the only process improvement methodology well-established and used across industries [27]. Thus, they are selected to inform the theme of process improvement recommendation.

Validate Themes & Discover Inter-Theme Relationship The practical aspect of our study focuses on validating the themes established from literature and analysing inter-theme relationship with real-world process mining case studies. By doing this, we are able to verify and refine the theoretical aspect with empirical evidence. It also enables us to ensure the findings are grounded in practice. In our current work, we focus on publicly available case studies to ensure truthfulness and reproducibility. We collect case studies from 3 major sources: Business Process Intelligence Challenge (BPIC)[3], the IEEE Task Force on Process Mining (TFPM)[4], and Business Process Management Cases [5, 23]. By reviewing the case studies, we analyse how process mining has been used and how process improvement recommendations have been proposed when addressing real-world problems, and discover the relationship (if any) between the proposed themes.

4 Establishing Themes[5]

4.1 Process Mining Analysis

Fig. 2 depicts the thematic map of process mining (PM) analysis, consisting of 12 sub-themes. **Process Discovery** builds procedural/declarative process models, or hybrid process models containing both [24, 34, 1, 22, 10]. **Process Model Enhancement** can *repair* the model to better represent the process executions [24, 14], or *extend* with additional data recorded in event logs (to enable further analysis) [24, 34, 16]. **Organisational Mining** involves *Organisational Structure Mining* for discovering the resource roles and hierarchical organisational structure [16], *Social Network Mining* for discovering the performers involved in a case and their relations [24, 1, 16, 22], and *Goal Mining* for discovering the process actor's intentions related to the execution of process activities [24, 8]. **Decision Mining** (*a.k.a.* Rule Mining) examines data attributes in event logs to elicit the rules behind the choices made in the process [24, 16,

[3] https://www.tf-pm.org/competitions-awards/bpi-challenge
[4] https://www.tf-pm.org/resources/casestudy
[5] Full-size thematic maps are available in a separate file on Google Drive, which can be accessed via https://tinyurl.com/bdcpw63j

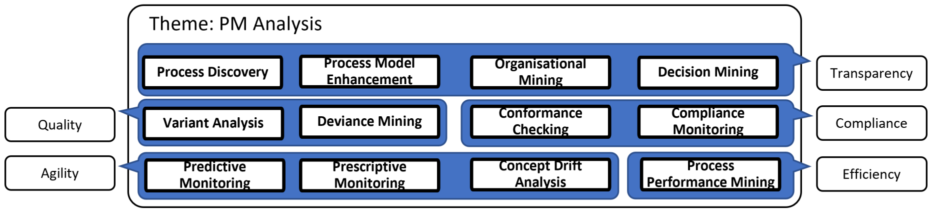

Fig. 2. Thematic map of PM Analysis

22, 21]. **Process Performance Mining** concerns *Execution Duration* [24, 1, 14, 16, 10], *Resource Utilisation* [24, 34, 1], *Outcome Quality* [24], *Performance of Connected Processes* [24], and *Performance Trends Over Time* [24]. **Variant Analysis** identifies process variants in an event log [24, 16, 22, 10, 33]. **Deviance Mining** discovers the reason behind a certain variant deviating from the most frequently taken path [24]. **Conformance Checking** examines if the actual process behaviour conforms with the expected behaviour [24, 14, 10, 11]. Similarly, **Compliance Monitoring** checks if the behaviour of active cases complies with predefined rules and constraints [24]. **Concept Drift Analysis** detects changes in the process behaviour over time [24, 16, 22, 6, 32]. **Predictive Monitoring** predicts the process outcome, risk and/or performance of active cases [24, 16, 22, 25]. **Prescriptive Monitoring** identifies specific interventions to improve the likelihood of a favourable outcome, or when an intervention is needed [24, 20].

The 12 sub-themes can be clustered into 5 groups [24]. Process Model Discovery, Process Model Enhancement, Organisational Mining and Decision Mining focus on *transparency*. Process Performance Mining focuses on *efficiency*. Variant Analysis and Deviance Mining are concerned with process *quality* in terms of how certain process traces may differ from common execution paths. Conformance Checking and Compliance Monitoring deal with process *compliance*. Predictive/prescriptive monitoring and concept drift focus on process *agility*.

4.2 Process Mining Technique

Fig. 3 depicts the thematic map of process mining technique, consisting of 10 sub-themes. **Process Discovery** has two different types: *Model-based Discovery* produces a graphical process map [1, 14, 22, 16, 24], and *Constraint-based Discovery* discovers textual process descriptions, e.g., declarative mining [1, 24]. **Variant Analysis** covers *Model-based Techniques* [16] and *Vector-based Techniques* [16, 33]. **Decision Mining** utilises *Decision-aware Techniques* [1] and *Classification-*

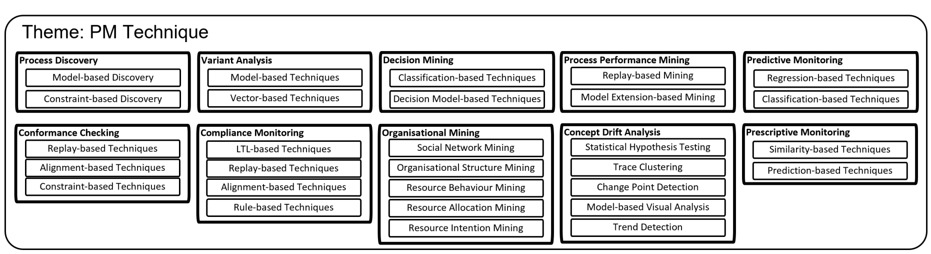

Fig. 3. Thematic Map of PM Technique

based Techniques [21]. **Process Performance Mining** mainly covers techniques based on *Replay* to support bottleneck identification and enable temporal analysis [1], and *Model Extension-based Techniques* to incorporate performance-related information to the control-flow and enhance process analysis [30]. **Organisational Mining** includes techniques such as *Social Network Mining* to discover the relationship between resources [1], *Organisational Structure Mining* to discover the organisational hierarchical structure [1], *Resource Behaviour Mining* to discover the behaviour of resources [1, 26], *Resource Allocation Mining* to discover the allocation of resources [13], and *Resource Intention Mining* (Goal Mining) to discover the intention of resources instead of the goal of the process and whether they are aligned [17]. **Conformance Checking** consists of techniques that are employed for conformance checking analysis, including *Replay-based Techniques*, *Alignment-based Techniques*, and *Constraint-based Techniques* [2]. **Compliance Monitoring** differentiates from conformance checking as it deals with active cases, though some techniques used for conformance checking can also be applied for compliance monitoring. **Predictive Monitoring** applies techniques based on *Regression* [25] or *Classification* [25]. **Prescriptive Monitoring** uses *Similarity-based Techniques* to recommend interventions based on completed cases that have yielded the same output [20], and *Prediction-based Techniques* to recommend interventions based on predicted outcome or performance for active cases [20]. **Concept Drift Analysis** encompasses six types of techniques [32]: *Statistical Hypothesis Testing* to compute the place of change and its characteristics (sudden drifts or gradual drifts), *Trace Clustering*, *Change Point Detection*, *Model-based Visual Analysis*, *Change Detection* to discover the process after change, and *Trend Detection* to identify the trend of drift.

4.3 Process Mining Outcome

Fig. 4 depicts the thematic map of process mining outcomes, consisting of 8 sub-themes. **Process Model** includes both *Graphical Model* mined by traditional process discovery algorithms [1, 14, 22, 16, 24] and *Declarative Model* by declarative algorithms [1, 24, 22]. **Process Variants** involves detected *Variants* [16, 24], *Differences & Similarities between Variants* [24, 16, 33], *Variant*

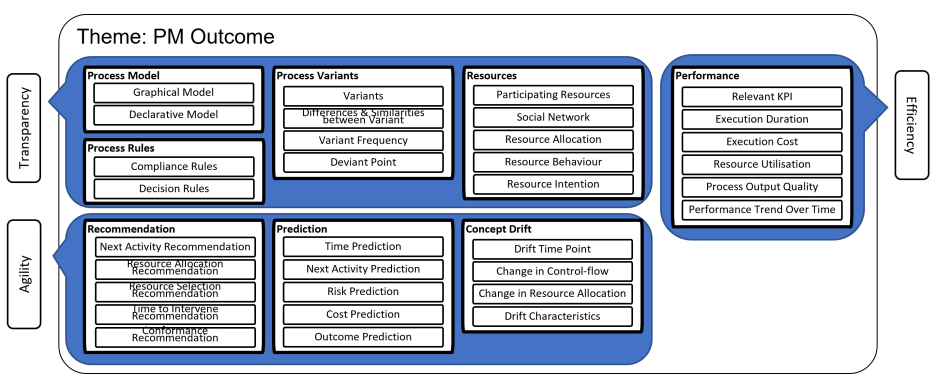

Fig. 4. The Thematic Map of PM Outcomes

Frequency [16, 33] and *Deviant Point* [24, 16]. **Process Rules** covers two types of rules, which are *Compliance Rules* [24, 16], and *Decision Rules* [24, 16, 21]. **Resources** include *Participating Resources* [24, 34, 16], *Social Network* [24, 34, 16, 1], *Resource Allocation* [24, 16], *Resource Behaviour* [1, 16], and *Resource Intention* [24, 8]. **Prediction** is the outcome produced by predictive monitoring, including *Time Prediction* [24, 22, 16, 25], *Next Activity Prediction* [24, 16], *Risk Prediction* [24, 25], *Cost Prediction* [24, 25], and *Outcome Prediction* [24, 16] of active cases. **Recommendation** is usually derived from the prediction, aiming for a favourable outcome or performance [14, 20], including *Next Activity Recommendation* [24, 16, 20], *Resource Allocation Recommendation* [14, 16, 20], *Resource Selection Recommendation* [24], *Time to Intervene Recommendation* [24], and *Conformance Recommendation* [24]. **Concept Drift** includes *Drift Time Point* [16], *Change on Control-flow* [16, 24], *Change on Resource Allocation* [16], and *Drift Characteristic* [16]. **Performance** related outcomes include *Relevant KPI* that reveal critical performance indicators for decision making [16], *Execution Duration* [24, 34, 16, 1], *Execution Cost* [16], *Process Output Quality* [24, 14], and *Performance Trend Over Time* [24].

The 10 sub-themes can be categorised into 3 groups. Process Model, Process Variants, Process Rules and Resources focus on process *transparency*. Prediction, Prescriptive Recommendation and Concept Drift focus on process *agility*. Performance focus on process *efficiency*.

4.4 Process Improvement Recommendation

The BPR framework and 29 best practices proposed in [31] are considered seminal work for process improvement, and are proven to guide the design of to-be processes with improved process performance [27]. Other papers we found about BPR are either on a too high level that only discuss methodology rather than how a process can actually be improved, or on a too specific level that is case by case. Thus, establishing the Process Improvement Recommendation theme differs from the other three themes. The existing BPR framework is transformed into a thematic map, as illustrated in Fig. 5.

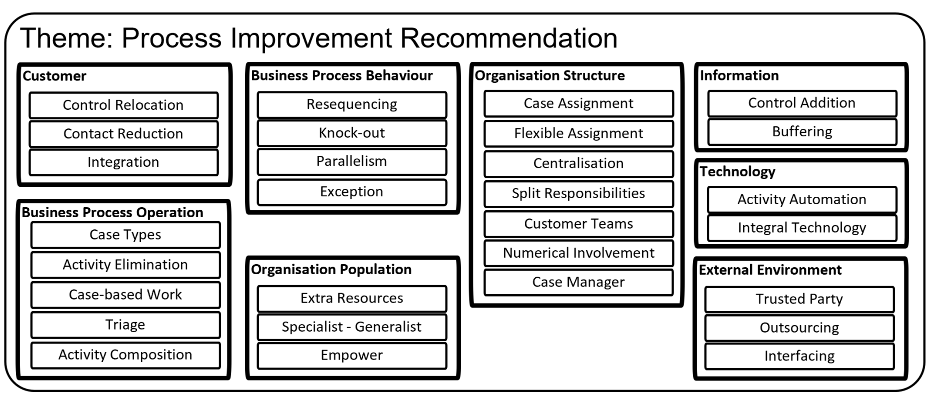

Fig. 5. Thematic Map of Process Improvement Recommendation (a representation of BPR best practices in [31])

5 Validation and Analysis

In this section, we refer to the case studies published in process mining to validate and where appropriate, further extend our findings from the literature. All case studies selected must analyse a business process using process mining techniques. Event log generation, evaluation of process discovery algorithms, and data pre-processing are not considered specific to process mining. A total of 156 case studies were selected, including 127 BPIC reports, 22 TFPM case studies, and 7 BPM case studies. The full list of selected case studies can be found on a companion file (see footnote 5). The BPIC is an annual process mining competition. Event logs are publicly available and provided to the contenders as the sole information source. Despite BPIC focuses on discovering and analysing the process, some contenders also tried to recommend process improvements, especially in the later years. The TFPM and BPM case studies represent real-world scenarios in which practitioners have access to additional information channels beyond event logs, and methods like interviews and questionnaires are also available.

In the case studies, we look for any process mining analysis, any process mining technique employed, any outcome deriving from process mining analysis, and any recommendations for process improvement. Then, we classify them according to the pertinent themes outlined in Section 4. If no process improvement recommendation is made based on a PM analysis, the theme is left blank.

5.1 Validation of Findings

Coverage and Awareness of Themes We did not find any new themes from the case studies analysis. Table 1 lists the frequency of PM Analysis used in case studies. Process Discovery is the mostly used process mining analysis among the selected case studies. Almost all case studies discover a graphical process model. The declarative model has only been identified twice in (Brandão *et al.*, BPIC2014) and (Jalali, BPIC2016). In fact, the process analyses in many case studies were purely based on process models. They discovered the model using pre-processed event log which fits their analytical purpose to conduct their analysis for different purposes, such as (Hevia and Saint-Pierre, BPIC2013) and (Radhakrishnan and Anantha, BPIC2013). Process Model Enhancement has not been identified from the selected case studies. It enables other analyses, such as the model-extension-based performance mining techniques, rather than providing analytical value itself. Some PM Analyses and PM Techniques appear to be less frequently used in our selected case studies. This may be due to the current coverage of case studies, as the majority of the selected case studies are from BPICs, which often include specific questions to be addressed. These questions clearly influence the decision on what process mining analysis to conduct.

Table 1. Frequency of each PM analysis in the selected case studies

PM Analysis	Frequency	PM Analysis	Frequency	PM Analysis	Frequency
Process Model Discovery	108	Process Performance Mining	92	Compliance Monitoring	7
Process Model Enhancement	0	Variant Analysis	86	Predictive Monitoring	19
Organisational Mining	54	Deviance Mining	23	Prescriptive Monitoring	1
Decision Mining	3	Conformance Checking	13	Concept Drift Analysis	22

Few Improvement Recommendations Guided by BPR Best Practices. Through the entire validation, only 42 case studies have clearly proposed process improvement recommendations that can be used to derive the theme. Among those, only (Bautista *et al.*, BPIC2012) made recommendations that were guided by the BPR best practices. Case studies from TFPM and BPM Cases are real-world cases where the practitioners were hired to solve real business problems. However, from these reports, we do not observe any information about how and to what extent the process was improved. Consequently, we are unable to use these reports to validate the Process Improvement Recommendation theme. Based on our observations, it is evident that there is still a divergence between process mining and BPR.

5.2 Relationship Discovered

The complete set of relationships discovered from the selected case studies is available in a separate file (see footnote 5). Below, we present some findings worth of discussion.

PM Analysis and PM Technique We observed an interesting connection between analysis and technique. Conformance checking techniques are used to identify variants (Caron et al, BPIC2011), and variant analysis techniques are used to check process conformance in (Hansen, BPIC2013). From the perspective of the techniques of variant analysis and conformance checking, they are very similar. The only difference between conformance checking and variant analysis is that conformance checking compares the variants against a reference model, but the variant analysis does not deem a variant as reference.

The work of (Paszkiewicz and Picard, BPIC2013) applied a model-based variant analysis technique to check if the cases followed the correct event order, which is a compliance rule. Thus, a connection between *Variant Analysis* techniques and *Compliance Monitoring* is identified.

BPIC 2013 requests contenders to analyse the "ping pong behaviour" in the process. The problem was interpreted differently by contenders. Some contenders, such as (Paszkiewicz and Picard, BPIC2013) and (van den Spiegel *et al.*, BPIC2013), tackle this question by importing the resource values from the event log as activity names to process mining software. The generated Directed follow graph captures the directional relationships between resources, instead of activities. This is seen as using the *Model-based Discovery* techniques to understand the problem. While others use *Social Network Mining* techniques to discover the handover of work between resources, such as (Hansen, BPIC2013).

There are also contenders who use Social Network Mining technique to discover the control-flow, such as in (Jalali, BPIC2016). The process in question captures the user behaviour of a website, which is relatively more complex in nature. The contenders set the activities as resources when importing the event log into the Social Network Miner in ProM. The chord diagram generated captures the connections between activities, which reflects how the users interact with the website. This indicates a connection between Process Model Discovery analysis and Social Network Mining technique.

PM Technique and PM Outcome Connections between PM techniques with PM Outcomes are mostly straightforward, e.g., Model-based Discovery techniques generate process models, and Predictive Monitoring techniques generate process outcome prediction, process time prediction, risk prediction and cost prediction. One interesting finding is that some contenders apply process mining algorithms designed for discovering process control-flow to mine social networks. In (van den Spiegel *et al.*, BPIC2013) and (Teinemaa *et al.*, BPIC2015), contenders replace the activity attribute with the resource attribute when importing the log into process mining software. They claim the resulting diagram generated by process mining software captures the handover of work between resources and thus presents a social network.

PM Outcome and Process Improvement Recommendation Suggesting process improvement recommendations is a complex task, which usually requires consideration of many factors within and beyond data recorded in event logs. In the selected case studies, practitioners made their recommendations usually based on multiple analytical findings. Table 2 lists several examples of connections between PM outcome and Process Improvement Recommendation.

While the discovered connections between PM Analysis, PM Technique and PM Outcome are relatively clear and strong, how PM Outcome relates to Process Improvement Recommendation is relatively weak. We do identify practitioners implementing process mining for process analysis, and their process improvement recommendations are made based on their PM outcomes. However, often the PM outcomes are not the mere source to derive process improvement recommendations. Some improvement recommendations are not only based on the PM outcomes but also on the relevant context and domain knowledge as well as findings from other analysis methods. For this reason, a valid Process Improvement Recommendation should be made based on multiple inputs and the PM Outcome is one of them.

As shown in Table 2, process improvement recommendations may be proposed based on more than one PM outcome, such as (Bautista *et al.*, BPIC2012). Also, it is possible that more than one process improvement recommendation are made due to one PM outcome, such as (González *et al.*, BPIC2020). This is potentially due to the fact that not all the required information is available in the event log and as a result, the analysts do not have sufficient information to make the most suitable recommendation.

Another interesting finding is different practitioners propose different process improvement recommendations for the same scenario. In BPIC2017, the contenders are requested to answer a question about the conversion rate between the applicants with one offer and those with multiple offers. Despite the different interpretations that have been made in different reports, different recommendations are made based on similar analysis outcomes. (Povalyaeva *et al.*, BPIC2017), (Fani Sani and Sotudeh, BPIC2017) and (van der Ham, BPIC2017) all think more offers would bring a higher conversion rate, but (Povalyaeva *et al.*, BPIC2017) suggest proposing more offers to applicants, (Fani Sani and Sotudeh, BPIC2017) have not suggested any recommendation regarding this finding, and

Table 2. Examples of connections between PM Outcome and Process Improvement Recommendation discovered from selected case studies. Refer to footnote 5 for access to the complete list of connections discovered from selected case studies.

Source	Sub-Outcome	Sub-sub-outcome	Explanation	Recommendation made	Related BPR Best Practice
(Bautista *et al.*, BPIC2012)	Resource	Resource allocation	Resource assigned to different activities	Recast generalist as specialist	Generalist-Specialist
	Resource	Resource utilisation	Specialists may be better at handling a large number of cases		
(Bautista *et al.*, BPIC2012)	Resource	Resource allocation	Fewer resources involved in a case, the case would last too long	Early termination of cases	Knock-out
	Performance	Execution duration	Slow moving cases are more likely to be rejected		
(Berger, BPIC2017)	Variants	Variants	Contact customer more times, cases are more likely get cancelled	Reduce the contact frequency with customer	Contact reduction
(Berger, BPIC2017)	Performance	Execution duration	Manual work takes too long	Digitise the application process	Activity automation
(Dmitry *et al.*, BPIC2020)	Variants	Variants	An unnecessary step is identified in some cases	Eliminate unnecessary steps for cases of a complete cancellation	Activity elimination
(González *et al.*, BPIC2020)	Resource	Resource allocation	Only 2 resources can approve applications	Authorise other roles for approval	Empower
				Increase the number of supervisors	Extra resource
(Elena *et al.*, BPIC2020)	Variants	Variants	Rework because of wrong input	Add standard fill-in instructions	Interfacing
(Filipov *et al.*, BPIC2020)	Variants	Variants	Too many payment events, creating double payments	Only pay after trip ends	Activity composition
(Pakileva *et al.*, BPIC2020)	Performance	Execution duration	Long waiting time due to peak hour	Consider allocate resources to peak time	Flexible assignment
	Resource	Resource allocation	Non-effective resource allocation and additional assignments		

(van der Ham, BPIC2017) suggest to provide more attractive offers to applicants with a high credit score.

Connections Across All Themes Despite the connection between PM Outcome and Process Improvement Recommendation is relatively weak, we indeed discovered connections that start from PM Analysis and end in Process Improvement Recommendation. In BPIC2015, the contenders were required to identify possible points for improvement in each municipality's organisational structure. The study of (van den Spiegel and Blevi, BPIC2015) tackled this question by analysing the relationship between resources. They found that some resources worked on the same cases, and suggested that assigning case ownership to a dedicated resource could improve the process. In such an example, the connection across all themes is clear; they conducted an *Organisational Mining* analysis (**PM Analysis**), used *Social Network Mining* technique (**PM Technique**), extracted *Social Network* (**PM Outcome**), and suggested *Case assignment* (**Process Improvement Recommendation**).

6 Conclusion

With an aim to establish the connection between process mining and BPR, we have established 4 themes — process mining analysis, process mining technique, process mining outcome, and process improvement recommendation. We have validated the proposed themes with case studies. Along the validation of the themes, we also managed to discover some connections between the themes.

The current work has a limited coverage of literature and case studies, resulting in potential threat to validity. Expanding the literature and case study coverage can mitigate this limitation. The proposed themes and discovered connections have not been tested in a real business context. We believe a field study could expose potential missing themes and dramatically increase their applicability. All these inform important agenda items for future work.

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