Fifteen years of process mining in Brazil: Current contributions, most used techniques, and challenges

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Abstract

Context: Process mining is a discipline that combines data science (data mining) and process science (Business Process Management - BPM), which has become crucial for large organizations as it enables the discovery, maintenance, and improvement of business processes. Problem: In the context of process mining in Brazil, there is a gap in the consolidated knowledge about the state of the art and the main topics being discussed. Solution: This study aims to understand what are the most frequent process mining techniques and challenges discussed within Brazilian research and the contributions to the advancement of the discipline in the country. IS Theory: This study was conceived under the aegis of Argumentation Theory, presenting information and evidence on selected studies and the results discussed. Method: A systematic literature review (SLR) from the last 15 years on process mining in Brazil was carried out, considering studies with Brazilian affiliation and using searches in scientific databases. Summary of Results: Through the analysis of 153 studies, we identified 9 different groups regarding Brazilian contributions to the advancement of the discipline in the country. By examining the results obtained, the methods applied, and the findings presented in the studies included on the SLR, we identified the most commonly used process mining technique in national research, as well as the main challenges cited by Brazilian authors, notably the need to address log quality. Contributions and Impact in the IS area: This study increases visibility of the current state of process mining research in Brazil in order to highlight new research opportunities within the Brazilian market.

CCS Concepts

• **Information systems**;

Keywords

Process mining, Brazil, Business Process Management, Systematic literature review, contributions, challenges.

1 Introduction

Information systems are constantly evolving and increasingly support the execution of complex business processes in organizations [44]. These systems often record large amounts of execution data, storing in event logs which activities were performed, when they occurred and by whom [48]. However, many organizations are unaware of the methods to extract value from this data, which could be used to assist in managing their business processes [44].

The use of business process models helps in understanding how processes operate, allowing analysts to discuss and identify improvements. To create these models, analysts can use manual discovery techniques, such as interviews with experts, document analysis, or observing process execution by participants [44]. However, these manual techniques have limitations that make discovery difficult. For example, in the observation technique, participants may speed up their activities due to being observed. In the case of interviews, experts may report different versions of the same process due to differences in perspective. Finally, the lack or outdated nature of information can limit document analysis [15].

Due to these limitations, manually discovered models may distort the reality of the process, providing only an idealized view. These distortions hinder process understanding and consequently increase the likelihood of misguided decision-making when attempting to analyze, improve, and implement processes [15]. To avoid the limitations of manual techniques, an alternative is to use process mining, which enables not only the automated discovery of processes through event log analysis but also process conformance checking and improvement [44].

In recent years, process mining has emerged and become fundamental for continuous process improvement in large organizations [44]. Its application is occurring in different sectors; in the healthcare sector, for example, De Vries et al. [13] uses process mining to support the verification of compliance between the process performed and the recommended process for the treatment of sepsis in a hospital. Similarly, Quintano Neira et al. [36] apply process discovery techniques to understand the real flow of sepsis treatment, aiming to improve comprehension of the executed process. In the manufacturing sector, Ruschel et al. [39] use process discovery to map operational-level processes, while De Oliveira et al. [8] combine process discovery and performance analysis to improve manufacturing processes through logs. In the area of software development, Lemos et al. [25], apply process mining to assess whether the process executed by the development team is aligned with the standard defined by the company.

Despite the diversity of sectors in the application of process mining in Brazil, there is still a gap in consolidated knowledge about the state of the art and the main topics debated in the national context. This gap refers to the absence of a study focused on process mining in Brazil, which compares the use of the discipline in relation to challenges and techniques, in addition to analyzing the contributions to its evolution specifically in the Brazilian scenario. According to the survey carried out by Peres et al. [34], Brazil ranks

12th in the number of publications on process mining, alongside countries such as India and South Korea, with a growth in publications since 2017. The research was based on data from the Scopus database. The study also revealed that, although the adoption of process mining is crucial for Brazilian organizations, they face challenges, mainly related to the high cost of implementation and the use of data, with an emphasis on privacy and security issues.

We conducted a preliminary survey on process mining in Brazil which revealed a lack of systematic literature reviews (SLR) that indicate the state of the art on this topic within the country. Because of this, it was unclear what challenges Brazilian companies and researchers face when using process mining. There are also questions about which mining techniques are predominant and what research contributions have been made.

This study presents the results of an SLR that mapped the studies published with affiliation in Brazil in the last 15 years (between 2009 and 2024). The research resulted in the analysis of 153 articles, covering a diversity of themes and approaches related to process mining in the Brazilian context. The review assesses the current Brazilian landscape on the topic, aiming to address the questions raised. As a result, the studies were classified into 9 groups regarding their contributions, clarifying how authors affiliated with Brazil are approaching the topic. The identification of the most used process mining techniques in the Brazilian research scenario, comparing the results with the global scenario presented in other SLRs, aiming to understand how and in which contexts they are being applied. Finally, our SLR provides the mapping of the main challenges faced by Brazilian researchers in implementing process mining and additionally, perspectives on how some of these challenges can be solved. Our analysis of the results shows the potential opportunities and the gaps in Brazilian research that might be explored in further studies and applications in this field.

The remainder of this paper is structured as follows. Section 2 goes over the discipline of BPM and Process Mining, providing background for the work that was developed and brings a discussion on related works. Section 3 presents in detail the methodology used to conduct the SLR, aiming to analyze the collected data and answer the research questions. The Section 4 the results obtained in carrying out the SLR are presented and discussed, based on the answers to the questions that comprise this study. Finally, the Section 5 concludes the study by presenting the main contributions and future directions.

2 Fundamentals and Related Work

In this section, the necessary foundations for conducting the study are presented. Initially, a review of the BPM concept is provided, along with the main concepts and theories related to process mining. Finally, three techniques and challenges of process mining are introduced and a discussion on related work is provided.

2.1 Business Process Management

A business process can be defined as a set of activities carried out to achieve business objectives. These activities are typically performed by different departments, people, and systems. Processes can be simple, such as a product sales process that begins when a customer places an order and ends when the product is delivered to the customer. In this case, the process involves few steps and minimal interaction with other departments and systems. Conversely, they can be quite complex, like the loan application process, which involves significant interaction with other departments and systems, such as credit verification, increasing the number of steps required for complete execution [15].

In this context, BPM contributes to the effective management of organizational processes [15]. Through BPM, a clear representation of business processes can be obtained, including their respective activities and the execution constraints between them [47]. The main objectives of BPM include supporting companies in decision-making, enhancing processes, increasing performance, and enabling continuous process improvement [15].

2.2 Process Mining

While BPM uses a proactive approach, focusing on modeling, analyzing, and improving business processes [15], the discipline of process mining, on the other hand, uses a reactive approach, centered on analyzing event logs of processes that have already been executed [44].

Event logs are essential elements for process mining, providing a detailed view of the activities carried out during process execution. A log can be defined as an ordered sequence of data records, in which each record is linked to a process instance and represents an event in that instance. When these logs are analyzed, it becomes possible to describe the behavior of a process through recorded executions [44].

The discipline of process mining focuses on enabling the analysis and interpretation of these logs [45]. It uses data science to collect and analyze large volumes of data (data mining) and process science (BPM) to add the necessary context to the extracted data to interpret process information [44].

Process mining can be applied using specific algorithms, many of which have already been implemented in tools available on the market. One of these is ProM, one of the main open-source process mining tools available. Other examples of tools include Celonis and Disco [44].

2.3 Process Mining Techniques

The techniques applied in process mining are used to discover processes, analyze bottlenecks, compare variants, suggest improvements, and verify compliance. They are divided into three categories: process discovery, conformance checking, and enhancement [44].

In the process discovery technique, event logs are analyzed to create a process model based on the data showing how the business processes was performed in practice. Process discovery can be considered a starting point for applying the other techniques [44].

Conformance checking aims to compare data from event logs with existing process models or business rule documentation to audit them. This technique helps identify which parts of the models are misaligned and require adjustments [44].

The third technique is process enhancement, which seeks to improve an existing process by using the model and event log data to generate an enhanced model. This new model may include additional activities, reduce existing ones, or incorporate additional performance and resource data [44].

2.4 Challenges of Process Mining

According to Aalst and Dustdar [1], it is essential for process mining analysts to consider the context in which events logs are generated. This context can significantly impact the interpretation and outcomes of the analysis. The challenges highlight the complexity of extracting accurate, actionable insights from event logs and include issues related to data quality, process variability, and the alignment between discovered processes and organizational objectives. The challenges identified by Aalst and Dustdar [1] served as a basis for answering RQ3 (Research Question 3), available in Section 4.3, with the aim of evaluating which of these obstacles are faced by Brazilian researchers and analysts in the field of process mining. Using this framework of challenges as a reference, it was possible to investigate to what extent each of the 11 challenges impacts the development and application of process mining techniques in Brazil.

By identifying these challenges, the authors Aalst and Dustdar [1] provide an overview of them, to help organizations transform raw event records into insights for process improvement and decision making. Eleven challenges commonly faced in the field were presented:

(1) *Log Quality*: The extraction of event data suitable for process mining is crucial. For example, the data should not be incomplete or have varying levels of granularity.
(2) *Log Size and Complexity*: The size of event log cannot be too large, as it becomes too complex to handle, nor too small, in which case it lacks sufficient data to draw reliable conclusions.
(3) *Benchmark Dataset*: The creation of good datasets with representative examples is necessary for comparing and improving process mining tools and algorithms.
(4) *Concept Drift*: Processes may change while being analyzed. When this occurs, mining needs to detect and adapt to these deviations.
(5) *Representational Bias*: A refined choice of representation bias is required, which means that careful selection must be made regarding the filter (set of event logs) to be used in modeling through process discovery.
(6) *Balance Among Quality Criteria*: Models produced by mining need to achieve good results balanced across four dimensions: adequacy, simplicity, accuracy, and generalization.
(7) *Mining Across Organizations*: Organizations working together may generate event data in different formats, complicating traditional process mining techniques.
(8) *Operational Support*: Process mining does not occur solely in an offline manner, so it is necessary to deal with online operational support.
(9) *Combining with Other Techniques*: There is a difficulty in combining process mining with other techniques, such as data mining and optimization.
(10) *Usability for Non-Specialists*: User-friendly interfaces are necessary for non-specialists to use complex process mining algorithms.
(11) *Understanding for Non-Specialists*: Results should utilize an appropriate representation for non-specialists.

2.5 Related Work

Several SLRs have been conducted in the context of process mining; however, none have affiliations in Brazil. For example, Zerbino et al. [48] analyzed 145 studies on process mining focused on the area of business management, revealing that process discovery is the most commonly used technique, followed by conformance checking, and lastly, enhancement. A survey of the most used algorithms in this business context was carried out, and the one that stood out the most was the Fuzzy Miner algorithm [48].

In El-Gharib and Amyot [16], 32 articles were analyzed in the context of robotic process automation (RPA), highlighting the importance of combining techniques for better understanding and automation. Additionally, Akhramovich et al. [2] conducted an SLR combining process mining with the context of Industry 4.0, analyzing 47 studies. They identified that the use of process mining supports the understanding of complex models and increases process efficiency. The most commonly applied techniques were again process discovery and conformance checking.

Recently, Mamudu et al. [29] developed, through a case study, a model with ten success factors in process mining while also analyzing their interrelationships. As a result, a guide was created to direct organizational investments, allowing for efficient resource allocation, reducing ambiguities, and supporting the understanding of project objectives. Furthermore, this guide aids in the proactive identification and mitigation of risks, facilitating decision-making regarding project initiation.

The related works emphasize the importance of considering the use of process mining across different sectors, analyzing where and how this discipline has been successfully applied. These studies show that process mining can offer valuable support in diverse areas, demonstrating its adaptability and relevance in different organizational contexts. Furthermore, studies that have been dedicated to investigating the most used techniques in process mining indicate a clear preference for the process discovery technique, which has been identified as the most frequent approach. However, none of them have affiliations or specifically address the Brazilian context. The aim of the present work is to provide a strategic overview of the application and research of process mining in Brazil. This literature analysis and the responses to the addressed questions can offer new perspectives for Brazilian companies and researchers. Thus, our SLR can increase the visibility of what is being done and create opportunities for studies in the Brazilian context.

3 Methodology

This section presents the planning and execution of the SLR aimed at identifying studies related to the use of process mining in Brazil. An SLR is a way to systematically assess the state of the art on a specific topic by surveying all available research relevant to a research problem [24]. Initially, we examined digital databases in search of other SLRs that could cover the intended topic. In the absence of previous SLRs, we developed a research protocol to gather all relevant studies.

Process mining is emerging as essential for continuous improvement in large organizations, enabling the discovery, monitoring, conformance checking, and optimization of processes through logs generated by organizational systems [44]. Despite the progress in Brazil, where this practice is being applied in different sectors, there is still a lack of studies that consolidate knowledge about the national state of the art and the main challenges, such as high costs and privacy concerns [34]. In the context of this research, the research questions (RQ) are:

RQ1 What are the Brazilian contributions to the advancement of research on process mining?

RQ2 What are the process mining techniques most commonly applied in Brazilian research?

RQ3 What are the challenges for implementing process mining in Brazil?

Based on these questions, two keywords were identified for creating the search string to be applied in digital libraries: "process mining" and the country of affiliation of the article, "Brazil." The search was conducted using these terms in both English and Portuguese. In English, the search string was formulated as: (("process mining") AND AFFILCOUNTRY ("brazil")).

No publication date range limit was set, resulting in the identification of articles covering the period from 2009 to 2024. In other words, the scenario of the last 15 years was analyzed in this study. The digital libraries were selected based on the presence of recent publications, and accessibility for reading the located studies. Therefore, the search strings were applied in the following libraries: Scopus, IEEE, Science Direct, Web of Science, Springer Link, ACM Digital, and SOL, with necessary adaptations made to the search string to meet the specificities of each search engine. Regarding the study participants, the protocol preparation stage was carried out by two authors, while the selection, analysis and result stages were conducted by the main author of the article.

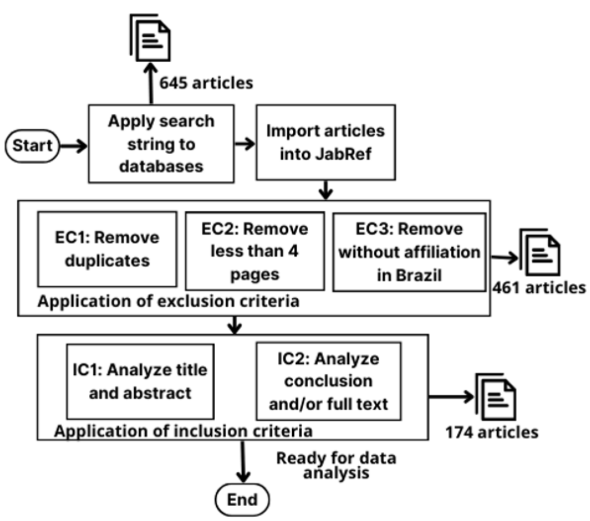

Figure 1: Flow of Research Protocol Implementation

The method for the study selection can be seen in Figure 1. It began with the application of the search string, which resulted in the identification of 645 articles. Due to the high volume of articles, the following exclusion criteria (EC) were established: duplicate articles (EC1); articles with fewer than 4 pages (EC2); and articles without affiliation in Brazil (EC3). EC3 was necessary due to the search characteristics of each database consulted, as not all of them have a specific filter by affiliation, such as Springer Link and SOL.

As for the inclusion criteria (IC), it was necessary to assess whether the articles were related to the field of process mining and whether they addressed the research questions. This criterion was applied starting with the analysis of the title and abstract of the articles (IC1) and, if necessary, extending to the analysis of the conclusion or the full text (IC2).

The articles were imported into the JabRef tool to assist in managing the application of the criteria. Through the exclusion criteria, 184 articles were removed. From the remaining articles, we selected 174 based on the inclusion criteria to continue with the review and answer the research questions. Of these 174 articles, we had access to the full text of 153 by the completion date of the review.

4 Results

This section presents the answers to the questions formulated in the protocol. We observed an increase in the number of publications related to the topic over the years, particularly between 2018 and 2023, when there was a significant growth that indicates an increase in interest in this area of research. In Figure 2, the number of publications found and analyzed in the last 15 years of process mining in Brazil can be seen. The lower number of publications in 2024 is due to the fact that the review was completed before the end of the year. Additionally, due to space limitations in this paper, not all studies considered in the extraction of studies and statistical data could be referenced and mentioned in the answers to the questions. To support the analysis, the tables with the set of studies corresponding to each question are available at: <https://github.com/tassianed/List-of-Articles> .

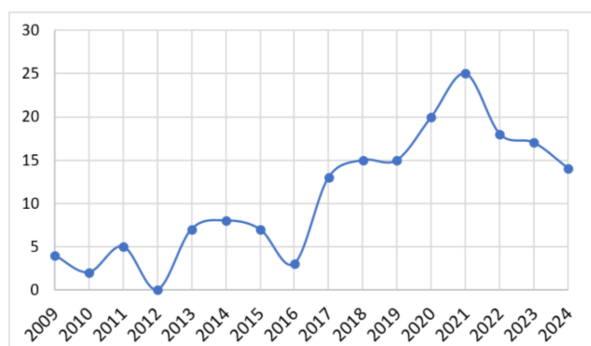

Figure 2: Number publications analyzed by year

4.1 RQ1 - What are the Brazilian contributions to the advancement of research on process mining?

Through the analysis of selected studies to address this research question, the contributions were categorized into nine groups. To perform a systematic categorization of the studies included in the review, a manual analysis of the articles was conducted, documenting and organizing the information in a structured manner. First, each study was summarized based on four main aspects: topics covered, methodologies employed, objectives and results obtained. These elements were extracted from each article to ensure a detailed understanding of its content and contributions. This division was developed by clustering the findings from the analyzed studies according to the principle of similarity. The classification was performed by comparing the studies based on common characteristics such as the topics addressed, methodologies employed, objectives, and results obtained. These shared features among the studies served as criteria to logically group the works. Some studies fit into more than one group.

The Figure 3 shows the total number of studies contained in each group. The groups with the greatest representation were those focused on creating new algorithms, approaches and tools, totaling 21.5%, followed by studies that focus on carrying out systematic and bibliographic reviews in the study area, totaling 20% of the studies.

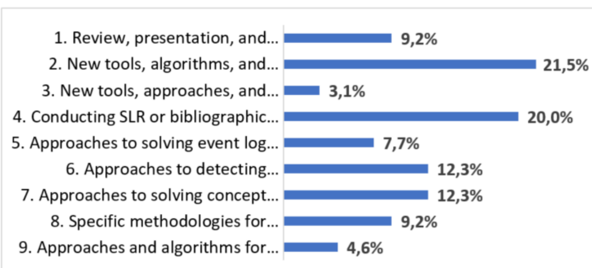

Figure 3: RQ1 - Number of articles per classified group

(1) *Review, presentation, and testing of existing tools and algorithms*: includes 9.2% of the selected studies. Here, we grouped those studies that aim to review and test process mining tools and algorithms that are already established in the market and in academia, highlighting the importance of understanding and improving their use. In this way, this group provides a review and grouping of data on tools and algorithms. For example, in de Vasconcelos et al. [12], a review of tools used in academia and the market was carried out, discovering that only 9 (Apromore, ARIS, bupaR, Celonis, Disco, EverFlow, Minit, ProM 6, and QPR) of 42 tools support the three process mining techniques: discovery, conformance checking, and enhancement.

(2) *New tools, algorithms, and approaches for process mining*: includes all contributions to the three process mining techniques. These contributions add great value to the Brazilian panorama and represent 21.5% of contributions. For example, Colonna et al. [5] proposed a new methodology for mapping process models that are represented in petri nets. Fantinato et al. [17] and Fantinato et al. [18] present and validate an algorithm for process discovery, called x-processes. Its creation was based on existing algorithms for process discovery. The goal is to generate process models with a high level of accuracy, prioritizing precision over speed in generation, especially in cases where model fidelity is essential.

(3) *New tools, approaches, and methodologies for evaluating results*: includes solutions for visualizing the results of mining techniques. Better visualizations may improve usability for less experienced users, which is one of the main process mining challenges [1]. This category, representing 3.1% of the results, contains only two studies [27, 28], which present a tool called VisInter4PPM that aims to support business analysts in understanding the generated models. An experiment was subsequently carried out using a data set from a business process of a financial institution.

(4) *Conducting SLR or bibliographic analysis*: includes studies that contain a comprehensive review of the research area. A large number of studies are part of this group, totaling 20%. Although they do not focus exclusively on the Brazilian context, they provide an overview of the issues addressed and help direct future research. Some studies that fit into this group were: [6, 38, 42] and these addressed SLRs related to specific topics. As in Dallagassa et al. [6] the SLR was carried out specifically on the use of process mining in the health area, in which the authors also used articles with affiliations other than Brazil. The findings revealed that the most used technique was process discovery, and the most used algorithms were Fuzzy Miner and Heuristic Miner. In Romero et al. [38], the authors focused on identifying through a bibliographic survey how some techniques, including process mining, can support the management of organizational change. The analysis was carried out through the correlation of terms, identifying that process mining, according to the survey of studies carried out in the review, is related to organizational changes. The authors Silva [42], addressed the topic of analytical intelligence in processes, focusing on data science for business. As a result, it was observed that most studies focus on investigating how analytical intelligence can support the application of process mining techniques.

(5) *Approaches to solving event log problems*: includes studies with suggestions for solving event logs problems, which are essential for process mining. A total of 7.7% of the selected studies are part of this group. The use of event logs with problems can generate processes that do not correspond to reality [1]. Schirmer et al. [41] proposed a visual filtering approach for event logs, to allow experts to explore the data and manipulate it as needed to make it viable for mining. Ceravolo et al. [4] propose a new approach for preprocessing logs, based on statistical inference, in order to improve them so that the process discovery process generates more reliable models.

(6) *Approaches to detecting anomalous traces*: includes studies that focus on identifying anomalous traces from regular traces in event logs. For example, Bezerra and Wainer [3] developed three new algorithms (threshold, iterative and sampling) to detect anomalies that are difficult to find in logs. A total of 12.3% of the selected studies are part of this group.

(7) *Approaches to solving concept drift*: includes studies that address concept drift, which is also one of the main challenges

of process mining [1]. Concept drift refers to the changes in business process behavior that can be discovered and analyzed while examining event logs [1]. A total of 12.3% of the selected studies are part of this group. Some studies [9–11, 43] in this group present different approaches for detecting concept drift using tracking clustering, which aims to simplify complex problems by grouping similar patterns.

(8) *Specific methodologies for business areas*: includes studies that propose new methodologies for specific areas, such as the judiciary, auditing, health, and industry 4.0, since existing approaches might be inapplicable or too complex due to their inherent characteristics. This group comprises a total of 9.2% of the studies analyzed.

(9) *Approaches and algorithms for process prediction*: includes studies that propose new solutions to predict the execution or completion time of a process, based on the history recorded in event logs. For example, Neubauer et al. [31] proposed a method that uses tracking clustering and the k-Means algorithm to predict the completion of incidents in an IT company. 4.6% of studies are part of this group.

The results show that Brazilian researchers are contributing to the evolution of process mining in Brazil, although in an incipient way. It is observed that there is a balance between revisions and innovations. However, there is a discrepancy in the approaches to process mining techniques: the focus is on new approaches to process discovery, while other techniques, such as conformance checking and enhancement, are little addressed. These nine groups can be considered evolutions because they represent advances in different dimensions of process mining research. They not only address central challenges in the field, but also bring technological innovations and expand the possibilities for practical application, both in Brazil and in global contexts. Although the studies are not limited to solving local problems or bringing innovations to specific gaps in Brazil, all the selected studies have Brazilian affiliations, evidencing the direct contribution of researchers from the country to the advancement of the field.

Finally, regarding the number of studies that provide an answer to this question, we found that of the 153 studies analyzed, only 65 contributed to the evolution of process mining in Brazil. This result corresponds to less than half of the studies analyzed, showing that Brazil still has a long way to go to achieve greater prominence on the international scene.

4.2 RQ2 - What are the process mining techniques most commonly applied in Brazilian research?

The answer to this question is based on the techniques presented in section 2.3: process discovery, conformance checking, and enhancement. The process discovery technique is the most used, being cited in 114 of the studies evaluated, as illustrated in Figure 4. This observation is in line with the results obtained in previous SLRs that covered scopes beyond Brazil [2, 48]. Thus, there is evidence that Brazil follows the international trend regarding the use of process mining techniques. For data analysis purposes, we compiled studies, sorted by year, that mentioned the use of each process mining technique. Figure 4 shows the frequency and trends in the use of the techniques over the past 15 years.

One of the possible reasons for the highest utilization rate of process discovery is due to the fact that as input it only uses the event log to generate a process model, which is required input for the other two techniques. Additionally, our review found case studies in which this technique is used to discover patterns in specific work environments, without process mining being the central theme. For example, Ruschel et al. [39] uses process discovery to improve the manufacturing industry by extracting logs from shop floor databases by modeling the business process and providing information about the activities performed.

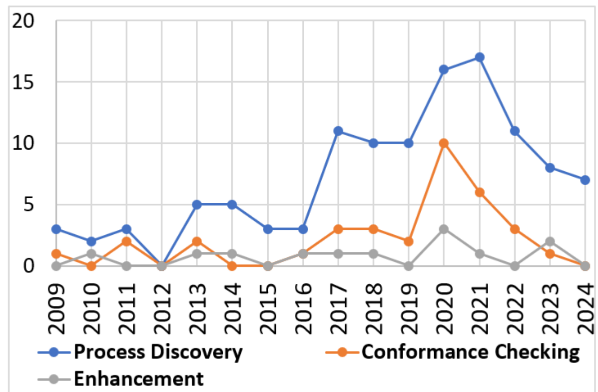

Figure 4: RQ2 - Number of articles used by techniques in the year

In some cases, the discovery was applied together with a performance analysis to optimize the processes involved. This combination was used for the sepsis analysis of a hospital [36]. Furthermore, the same combination was applied using data from the physical world to define the process model in the context of manufacturing, with the objective of optimizing the discovered processes. [8].

In some studies, such as Ferronato et al. [20], more than one technique was applied. In this example, process discovery and conformance checking techniques were applied to support the creation of a framework for decision-making. Another example is Pereira et al. [33], in which the three techniques were employed in a specific methodology that guides the application of process mining in the health area.

In Figure 4, it can be seen that conformance checking is the second most used technique. Neubauer et al. [30] use the conformance checking to compare behaviors recorded in logs made available by a transparency portal with the ideal models available, with the aim of promoting transparency and encouraging the use of process mining by the population. Still on the subject of conformance checking, in Lemos et al. [25], the technique was applied to assess whether the processes executed in a software development company followed the standard prescribed by them. The aim was to reduce the need for manual quality audits. In this case, the process discovery technique was also applied to obtain the model of the executed process.

Finally, the enhancement technique was used in studies such asGerhardt et al. [22], in which the discovered models were enriched with new details (for example, grouping activities that were repeated and caused loops, generating delays in the process), to carry out execution tests of the new model, with the aim of analyzing whether the new adjustments made the model perform within the expected time. The objective of the study was to verify factors that delayed the reimbursement process for services provided in healthcare sector.

In Pegoraro et al. [32], process discovery and enhancement are used to support management in decision-making regarding the flow of patients arriving at an emergency room. Through process discovery, it was possible to have a process model of how patient care takes place, and thus, analyses were performed to obtain statistics on the time required for each activity in the process. Through the results obtained in these analyses, improvements could be implemented in the process model, and then, new tests with the new model were performed based on simulations.

In the vast majority of years, conformance verification was cited more than enhancement, but, in general, conformance verification was the second most used in publications with Brazilian affiliation, followed by enhancement. Despite having less emphasis on enhancement studies, the technique plays a crucial role in process optimization. The studies by Gerhardt et al. [22] and Pegoraro et al. [32] show that it can lead to significant enhancement in terms of reducing process execution time.

By analyzing the answers to this question, we have shown that the combined use of techniques is recurrent. In at least 28 studies, two or more techniques were applied together. This shows that one technique can support the application of another. We have also shown that the application of process mining techniques has varied contexts. The examples analyzed range from the healthcare sector [13, 36], to the manufacturing sector [8, 39], as well as in the area of software development [25]. In addition to these, many other business contexts benefit from the use of process mining (such as in the auditing or judicial sectors).

4.3 RQ3 - What are the challenges for implementing process mining in Brazil?

A comparison was made between the process mining challenges encountered in the SLR with the 11 challenges cited by Aalst and Dustdar [1], as described in Section 2.4. In this question, a study may cite more than one challenge, so in some cases, the same article appears linked to more than one challenge. Of the 153 articles analyzed, only 31 times were any challenges mentioned during the implementation of process mining.

The most cited challenge, cited by 17 articles, was the quality of the logs extracted from the information systems and the need to adjust them before applying process mining. This need is frequently called preprocessing or data organization, and this step occurs because of the importance of ensuring the quality of logs before performing analysis [44]. The authors cite problems such as lack of event recording, errors, incorrect formatting, and inaccuracy in the date and time of events [13, 19, 26, 35, 40]. In addition, there is a need to verify data quality, as it is necessary to eliminate noise in cases in which they are incomplete [32]. For example, in Do Prado

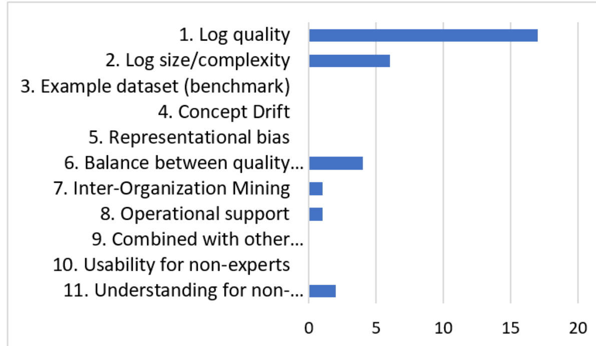

Figure 5: RQ3 - Challenges of process mining

et al. [14], in addition to adjustments to incomplete data, there was also a need to create a case ID to identify groups of logs to be evaluated individually.

The second most cited challenge is the size and complexity of the logs, which is also related to the need to manipulate event logs before applying process mining. In Garcia et al. [21], when first loading of logs, more than 8 million events were identified, which became a challenge due to the large volume of distinct transitions. In this case, the authors felt the need to reduce the number of logs by applying a filter to obtain data from only one of the branches of the analyzed company. In Vercosa et al. [46], the authors cite the complexity of dealing with unstructured logs, emphasizing the need to adjust data granularity as an essential step to enable process mining. The study focuses on the judicial context, where the lack of control over the sequence and nature of procedural movements makes logs highly unpredictable and heterogeneous. This characteristic reinforces the importance of preprocessing techniques to organize, filter, and transform data in a way that allows for more accurate analyses aligned with the objectives of process mining.

The third most cited challenge was the balance between the quality criteria of the process models generated by automatic process discovery. In this case, the lack of standardization in the logs can generate inaccurate process models, that is, models that do not represent the real behavior of the process. One such example happens in Ruschel et al. [39], in which the logs were not structured. Goncalves et al. [23] also cite the inaccuracy of the generated models, where a business process incorporates human and interactive activities, and in these cases, they will not be in the event logs, causing distortions of reality in the model.

Two studies highlight the challenge of understanding by non-experts. In D'Castro et al. [7], the authors point out the need to have an expert to interpret and validate the results when using the logs of a judicial system, ensuring that the generated model makes sense. In Riz et al. [37], the lack of knowledge about business rules presents an additional obstacle, requiring external support to understand the models produced.

In Dallagassa et al. [6], the authors face two challenges: performing process mining between organizations and operational support. They analyze healthcare processes that contain the use of different systems by different organizations, thus, the data generated is not standardized. The authors cite that the different standards make process mining difficult. In addition, there is a need for continuous and online operational support for the implementation and support of these systems.

Finally, five challenges were not mentioned by any of the studies analyzed in the SLR: the benchmark dataset, concept drift, representational bias; combination with other techniques; and usability for non-experts. This analysis highlights the challenges less frequently faced in the area of process mining in Brazil.

To answer this research question, we adopted an approach that identifies authors who mentioned having faced these challenges in the practical implementation of process mining. We then observed the need to include a secondary question to incorporate studies conducted by Brazilian authors who can contribute with discoveries and solutions to these challenges. The question formulated for this purpose is: Research Question: **What are the perspectives for solving these challenges?**.

To answer this question, we rely on the groups created in 4.1 and the challenges addressed in Section 4.3. Among the eleven challenges cited by Aalst and Dustdar [1], only four have Brazilian contributions to their resolution or mitigation. The four challenges are related to the following groups of contributions (as they were defined in Section 4.1):

- (1) *Log quality* and (2) *Log size and complexity*: To mitigate the problems in handling event logs prior to process mining, the studies of our fifth contribution group, "*Approaches to solving event log problems*" can be related to these challenges. Although 51.51% of the studies report difficulties with event logs, only 7.9% propose specific solutions to these challenges. This discrepancy highlights significant gaps that still need to be addressed to improve the efficiency of logs.
- (4) *Concept Drift*: Our seventh contribution group, "*Approaches to solve concept drift*," brings together studies focused on mitigating concept drift problems during process mining. Although no author has mentioned this challenge in practical implementation, some studies propose new approaches to address it.
- (11) *Understanding for non-specialists*: in this case, our third contribution group, "*New tools, approaches, and methodologies for evaluating process mining results*" dealt with studies that focused on solving questions for evaluating process mining results. We identified that only two studies were part of this group, which represents only 3.1% of the results.

As shown in Figure 5, it can be seen that challenges (1) and (2) were cited more frequently than the others. Other topics, such as balance between quality criteria, inter-organization mining, operational support, and understanding for non-specialists, were also addressed, although with less emphasis. Five challenges were not cited in any of the studies analyzed. Although there is recognition of relevant challenges in the area of process mining in Brazil, most of them still lack a more in-depth approach by the academic and professional community. Of the eleven challenges identified by Aalst and Dustdar [1], only four receive Brazilian contributions, focused mainly on the quality and complexity of logs, concept drift, and understanding of models for non-specialists. This reveals a considerable gap in the creation of practical solutions for the other seven challenges, which continue with few or no specific contributions.

5 Conclusion

This article presented an SLR to investigate the state of the art regarding process mining in Brazil over the last 15 years. The steps of the research planning and conducting methodology were detailed, allowing for its reproduction. Data from 153 studies were analyzed, and the results were summarized.

Regarding the number of studies analyzed, there is a limitation concerning 21 of them, for which access could not be obtained by the review completion date. However, it is understood that this limitation does not compromise the results obtained. Regarding the Brazilian contributions to the advancement of research, nine groups were created, and each of them was specified. It was noted that of the 153 studies developed, only 65 (less than half) pointed to the evolution of process mining in Brazil, indicating that there is still much to be developed in the country. The initiatives to create new approaches and review existing ones are balanced.

Process discovery was identified as the most used technique in the Brazilian scenario, followed by conformance checking, and, lastly, improvement. This result is in line with that of other SLRs, even if they did not have the limitation of Brazilian affiliation. In this case, we understand that process discovery receives more attention, as it is the technique that generates the model, an item necessary as input for the other techniques.

Regarding the challenges for the implementation of process mining, 6 of the 11 challenges listed by [1] were cited. The challenge most frequently presented by the articles found in the SLR was the quality of the logs, highlighting the need for adjustments in the extracted data. The second most cited challenge also concerns logs, which is related to the size and complexity of the extracted data. In this question, additionally, the challenges mentioned in Brazilian research were compared with the contributions made to address them. Although these challenges are globally recognized and cited by some Brazilian authors, the analysis of the studies found in this RSL indicates that there is still a significant gap in addressing and solving these problems in Brazil. Only four of the seven cited challenges by the studies that are part of this SLR, have prospects for resolution in the national context.

The nature of an SLR can be considered a threat to the validity of the work due to the exhaustive search characteristic. During the study selection process, there is a risk of selection bias, where relevant articles may have been omitted, either due to limitations in the search criteria or research sources. The interpretation of the data and the categorization of the studies may be influenced by interpretation bias, especially when it comes to subjectively classifying the studies into different categories. However, it is important to highlight that the methodology employed for conducting the SLR was planned and executed with the aim of minimizing these risks.

Potential future work consists of conducting an analysis of Brazilian companies that use process mining through interviews or other methods. The objective is to obtain data on the maturity level regarding process mining and to validate the success rates of its implementation in Brazil. In addition, from the data collected in these assessments, it will be possible to compare the results obtained with those presented in this SLR. The groupings, especially for RQ2, could be further refined by considering aspects of the usage context, enhancing the results and providing more details about process mining techniques.

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