Fairness for Process Mining: A Systematic Literature Review

Rachmadita Andreswari[1,2,4], Stephan A. Fahrenkrog-Petersen[2,3], Jan Mendling[1,2]

[1] Humboldt-Universität zu Berlin, Rudower Chausee 25, 12489 Berlin, Germany
[2] Weizenbaum Institut, Hardenbergstraße 32, 10623 Berlin, Germany
[3] University of Liechtenstein, Fürst-Franz-Josef-Strasse, 9490 Vaduz, Liechtenstein
[4] Telkom University, Jl Telekomunikasi 1, 40257 Bandung, Indonesia
{rachmadita.andre.swari,jan.mendling}@hu-berlin.de,
stephan.fahrenkrog@uni.li

Abstract. Process mining is a powerful tool for process improvement. This paper looks at improving the fairness of processes, one important aspect of social sustainability. It presents a systematic review of process mining research on fairness. In this paper, we address this research problem. More specifically, we conduct a systematic literature review to summarize the current state of research regarding fairness-aware process mining. We employ the PRISMA methodology to scan and evaluate the literature. We identify and review a total of 42 relevant papers and provide an analysis of the themes and topics covered in these papers. The review shows that challenges remain in balancing fairness measurement across qualitative, quantitative, and mixed-method research. Only 6% of the papers explicitly report fairness detection methods, 15 mention fairness metrics implicitly, and the remaining 15 do not address fairness metrics at all. These findings may provide valuable insights for researchers and practitioners, offering guidance on designing procedural justice and reducing bias.

Keywords: Fairness · Business Process · Process Mining.

1 Introduction

Fairness [22] is a central pillar of social sustainability and responsible process mining [20]. Recent works have expanded the scope of Responsible BPM by exploring benevolent business processes and proposing design guidelines beyond transactional value [32], as well as developing socially sustainable business process patterns [34]. Fairness is concerned with identifying bias of business process analysis and design. More specifically, fairness-aware process mining aims at preventing that bias in order to improves trust in systems but also ensures that business processes reflect inclusive and fair practices. Fairness also links to environmental and economic sustainability; for instance, equitable resource distribution can reduce unnecessary consumption, and inclusive process design can have an impact on long-term organizational performance and economic resilience.

In machine learning, fairness concerns have been studied across a wide range of decision-making scenarios that have significant implications for individuals and society [22], including financial lending [16, 40], and hiring [2, 36]. Fairness issues in process mining differ from those in machine learning. In machine learning, structured input-output data attributes are used for prediction, primarily to mitigate bias in training data. In contrast, process mining relies on event logs to analyze fairness in decision-making within sequential processes. In process-oriented research, fairness is often examined through the lens of organizational justice, which distinguishes three complementary dimensions: procedural fairness (e.g., consistency and transparency of rules), distributive fairness (e.g., equitable outcomes), and interactional fairness (e.g., respectful treatment) [14]. Additionally, fairness approaches in machine learning cannot be directly applied to process mining, as fairness in process execution is related to factors such as process variation, resource distribution [26], process compliance, and performance targets. An overview of research on process mining and fairness is missing so far. Following Rawls' conception of "justice as fairness" [31], fairness is not moral neutrality but the equal respect and consideration of all individuals. In the context of process mining, fairness concerns focus on identifying and mitigating bias in business process analysis and design. Fairness-aware process mining therefore aims to prevent such bias, thereby improving trust in systems and ensuring that business processes reflect inclusive and equitable practices.

This paper presents a PRISMA [23] literature review on fairness in process mining, summarizing current developments, outlining future research opportunities, and addressing the following research questions:

RQ1 What are the key themes, trends, and methodologies employed in research related to fairness algorithms in business processes and process mining?

RQ2 How have fairness algorithms been defined, developed, and evaluated within the domain of business processes and process mining, and what common metrics and benchmarks are used to assess fairness?

RQ3 Which fairness algorithms are currently utilized in Process Mining?

RQ4 What challenges and limitations are commonly associated with fairness in Business Processes and Process Mining, and what strategies have been proposed to address these issues?

RQ5 What insights and best practices can be extracted from the reviewed literature to guide future research and practical implementation of fairness algorithms in process mining systems?

Our review shows that fairness research in process mining is still emerging, mainly conceptual with limited empirical work, few implemented algorithms, and scarce real-world data. Fairness is often seen as bias mitigation or procedural justice but lacks metrics. We highlight best practices and future research directions for fairness-aware process mining.

The remaining paper is structured as follows. Section 2 outlines our methodology following PRISMA. Section 3 shows our results and Section 4 discusses them. Finally, Section 5 concludes and highlights opportunities for future work.

2 Methodology

We designed our research method to address the challenge of providing an overview of works on process mining and fairness. We used the PRISMA [23] systematic literature review method (see Figure 1). We performed the following steps:

Eligibility criteria. We searched the literature for relevant studies. From the databases we used the search term "fairness" AND "process mining", "fairness" AND "business process", and for the Scopus database we used keywords "business process fairness" OR "fairness process mining" OR "discrimination in business process", "discrimination process mining".

Information sources. We used the databases Google Scholar, IEEE, ScienceDirect, SpringerLink, DBLP, and Scopus as the basis for our review.

Search strategy. As a first step we selected all publications that contain both keywords. We only include research papers in our search that have been published between 2013 and July 2025, and identified a total of 5,570 papers.

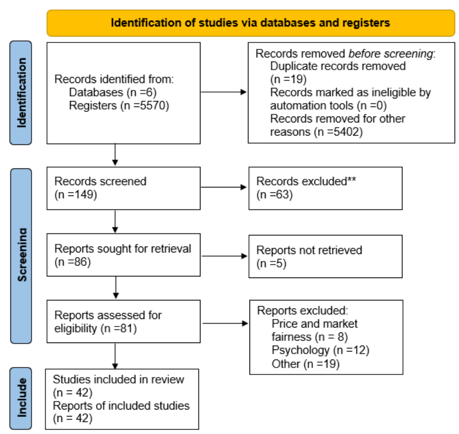

Fig. 1. PRISMA Methodology for Fairness in Process Mining

Selection process. We removed duplicate papers and excluded non-categorical papers that were out of scope. For each of the remaining papers, we screened and retrieved each record. We concluded inclusion based on the paper's relevance to fairness in business processes, process mining, and the availability of the full paper.

Data collection process. For data collection, one author gathered data from each paper, both manually from various databases and using the Watase application[5]. All coded data, screening decisions, and the BibTeX of the 42 included studies are openly available in a repository [6].

Data items. From all the data collected, we identified outcomes based on attributes specified by the research questions. In each study, we sought information regarding the key themes, methodology, level of development, scope, metric, case study, algorithm, tools and event log. Each outcome was categorized into specific attributes. If relevant information was missing, we noted it with "not specified." The goal was to exclude papers that did not directly contribute to process mining and business process management in terms of fairness. In this step we eliminated

[5] https://www.watase.web.id/home/index.php

[6] https://doi.org/10.5281/zenodo.17141300

a further 63 papers and ended up with 86 papers that we consider for retrieval. From the initial 81 papers retrieved for full-text screening, we excluded 39 papers based on the reasons listed above. As a result, 42 papers were included for final analysis.

Study risk of bias assessment. To minimize misunderstandings and potential assessment bias, all authors contributed to the process. The first author analyzed all included papers. The second author then evaluated the results and provided feedback on filtering and additional categorization to gain further insights from the findings.

Synthesis methods. In this process, each collected publication was analyzed based on the research questions, with decisions made on inclusion after reviewing titles, abstracts, and content. Graphs and tables were created to visualize data, with formats such as bar charts, pie charts, or tables chosen based on the data type, using Google Sheets for visualization. Bias assessment was performed to evaluate potential reporting biases through sensitivity analyses, and certainty assessments were conducted to ensure consistent and reliable findings across diverse studies.

3 Results

This section first presents general information about the topics of reviewed papers in Section 3.1 as well as method and underlying theoretical concepts in Section 3.2. Next, we provide a detailed analysis of how fairness-aware process mining has been studied in Section 3.3. Finally in Section 3.4, we explore the challenges, limitation and insight when applying process mining techniques to ensure fairness in business processes.

3.1 Topical Distribution of Studies

Overall, there has been a substantial rise of interest in the topic since 2016. As research on fairness in process mining continues to grow, the existing literature can be grouped into different focus areas.

Group 1: **Fairness in Data-Driven Decision-Making** explores bias in automated decision-making, particularly in areas like hiring, policing, and finance. Studies in this group also examine how fairness is perceived in human-machine collaboration, ethical concerns in automatic processes, and gender or socioeconomic biases in career progression. Researchers in this area commonly use algorithmic fairness assessments [15], [5], [38], [7] surveys [29], and case studies [12] to analyze these issues.

Group 2: **Ethical & Legal Considerations** focuses on fairness in legal and educational settings [3], [24], [17] including how fairness is addressed in policies and regulations [15], [33]. Studies in this group often use policy analysis [15], [24], interviews [37], [18], and experiments [39], [7] to understand how fairness is perceived and implemented.

Group 3: **Bias Mitigation Strategies in Process Mining** looks at ways to reduce bias in process mining [28] and ensure fairness in business process management [37]. This research often involves analyzing event logs [26], [25], applying fairness-aware machine learning techniques [40], [27], and using simulations to test different fairness strategies [20].

Group 4: **Future Research Directions** focuses on challenges in fairness-aware process mining [25], [37] trust in decision-making [28], [8] and future improvements in fairness methodologies [37], [27]. Studies in this group explore ways to enhance fairness in systems across different industries, such as finance [40], [38], [8]. Researchers commonly use conceptual frameworks to propose new fairness models [30], [10], [5], [27] and experimental models to test fairness-aware improvements [2], [5], [8], [4].

These groups highlight the increasing focus on fairness, policy-making, and business process mining. They also show the need for further research to develop better fairness methodologies, improve trust decision-making, and address emerging challenges in fairness-aware business process.

3.2 Research Methods and Theoretical Concepts

Different research methods have been used to study fairness and process mining. **Quantitative methods** are used predominantly, accounting for 57.1% of studies, particularly in recent years, reflecting a data-driven approach to analyzing fairness within business processes. However, there is a growing interest in **mixed methods** (combining qualitative and quantitative approaches), around 26.2%, emphasizing the importance of both numerical data analysis and contextual, qualitative insights. **Qualitative methods** accounts for a share of 16.7%.

Within this classification, design science or engineering-oriented research can span both categories depending on its focus. If a study primarily involves theoretical framework development, conceptual modeling, or case-based evaluation, it aligns more closely with qualitative research. Conversely, if it includes empirical validation, performance measurements, or statistical evaluation, it is classified as quantitative research.

Additionally, we conducted a deeper analysis of the research types employed in the papers, categorizing them into theoretical, empirical, and mixed approaches. The results indicate that the majority (78.6%) use an **empirical approach**, while 9.5% focus solely on **theoretical research**, and 11.9% **combine empirical and theoretical methods**.

Based on fairness concepts, individuals involved can be categorized into two levels: individual and population (group and organization). This classification arises because fairness can be perceived both personally and collectively within a group that shares similar characteristics. Addressing fairness at each level requires different approaches, as the perception and impact of fairness vary depending on the context. In our review, 28.5% of the cases focus on the individual level, 61.9% on the population level, 5% use a combination of both and the remaining 5% were not specified.

Business processes and process mining relate to the three fairness dimensions of procedural, distributive, and interactional justice. *Procedural justice* concerns the structure of processes, where process mining techniques can assess fair execution paths and decision points [1]. *Distributive justice* appears in how resources and workloads are allocated, which can be analyzed through event logs to detect unfair patterns [21]. *Interactional justice* focuses on stakeholder interactions, where mining reveals communication flows and handoffs [19]. Applying these justice types helps organizations design processes that balance efficiency and fairness at both individual and organizational levels [6, 11].

The data in Table 1 shows how different aspects of **procedural justice** are distributed. The most common approach (19 cases) combines formal procedure characteristics with explanations of procedures and decision-making. The second most common (8 cases) includes formal characteristics, explanations, and interpersonal treatment. Individual elements appear less frequently, with formal characteristics alone and explanations alone each occurring about 6 times. Categories involving interpersonal treatment or explanation of procedures and decision making are least common (2-4 cases), while "not mentioned" category account for about 2 cases. The data indicates organizations tend to implement procedural fairness as a multi-dimensional concept rather than focusing on isolated aspects.

Table 1. Percentage of Procedural Justice:
(a) Formal characteristics of procedures
(b) Explanation of procedures/decision making
(c) Interpersonal treatment

Procedural Justice	**Total**	**%**
(a)	6	14.29%
(a), (b)	19	45.24%
(b)	4	9.52%
(a), (b), and (c)	8	19.05%
(b), (c)	1	2.38%
(a), (c)	1	2.38%
(c)	1	2.38%
Not mentioned	2	4.76%

The analysis of distributive justice (see Table 2) shows that Equity and Equality dominate, together covering over 80% of the cases. This indicates that discussions of fairness in process mining primarily rely on well-established distributive justice principles. By contrast, Needs-based perspectives appeared only once, underscoring their marginal role. The small share of studies without explicit reference to distributive justice principles (4.76%) further suggests that most researchers implicitly anchor their work in these normative frameworks.

Table 2. Percentage of Distributive Justice

Distributive Justice	**Total**	**%**
Equality	20	47.62%
Equity	14	33.3%
Equity, Equality	2	4.76%
Equity, Needs	2	4.76%
Equality, Needs	1	2.38%
Needs	1	2.38%
Not mentioned	2	4.76%

The majority of studies (66.6%) did not explicitly integrate fairness as a systematic component, often mentioning it only as motivation or limitation. For example, Qafari et al. [28] mention fairness as part of the evaluation, but do not provide explicit mechanisms to enforce it in the process model. This shows that fairness implementation often remains incomplete within process-oriented systems.

This gap in fairness development integration is further reflected in the distribution of fairness research across various sectors, highlighting distinct patterns in how **different industries** approach the issue (see Table 3). Governance (16.67%) and human resources (14.29%) are the most represented categories, reflecting a particular interest in fairness within these fields. Finance and education each account for 11.9% of the studies, while healthcare accounts for 9.52%. Technology and law are each represented by 7.14%. Manufacturing accounts for 4.76%. Insurance and artificial intelligence each account for 2.38%, while multi-sectoral (combined) studies make up 11.9%. This indicates that while fairness algorithms are being explored in a wide range of industries, governance and finance have been main points, possibly due to their regulatory nature and social impact.

The analysis of **fairness metrics** in existing studies (see Table Table 4) reveals that only 21% explicitly specify fairness metrics (demographic parity, individual fairness, equalized odds, and disparate impact), while 40% potentially incorporate them without clearly defining their criteria. Meanwhile, the remaining 38% do not employed any fairness assessment criteria. These findings indicate that nearly half of the studies implicitly consider fairness metrics but fail to explicitly articulate them.

Table 3. Distribution across Sectors

Case Study	**%**
Governance	16.67%
Human Resources	14.29%
Finance	11.9%
Education	11.9%
Healthcare	9.52%
Technology	7.14%
Law	7.14%
Manufacturing	4.76%
Insurance	2.38%
Artificial Intelligence	2.38%
Combination	11.9%

3.3 Fairness Techniques in Process Mining

The issue of fairness in process mining differs fundamentally from fairness in machine learning. In ML, fairness is typically addressed through structured input–output attributes, where bias often arises from data curation and labeling practices in training datasets. By contrast, process mining is descriptive at its core, relying on event logs to reconstruct and analyze sequential processes. Removing or altering event data to enforce fairness would undermine the completeness of the process description. Therefore, fairness in process mining is assessed through process variants, resource allocation [26], compliance, and performance metrics, making its implementation conceptually distinct from ML approaches.

Table 4. Fairness Metrics Identified in Case Studies

Metrics	**Total**
Demographic parity	3
Equalized odds	3
Individual fairness	2
Disparate impact	1
Demographic parity (pot.)	6
Individual fairness (pot.)	5
Equalized odds (pot.)	3
Equalized odds, Individual fairness (pot.)	1
Demographic parity, Disparate impact (pot.)	2
Not specified	16

To explore the implementation of fairness in process mining, this study categorizes the literature into three perspectives. The largest share (52.4%) falls into general process analysis, where fairness is considered at a broad level of process execution and management. Within Business Process Management (BPM), 19% of the studies integrate fairness concepts, typically as part of broader BPM frameworks rather than as a primary focus. In contrast, 28.6% of the studies address fairness directly in process mining, specifically within process discovery, conformance checking, and enhancement.

Based on the studies, **fairness algorithms** are employed in the context of business processes and process mining; however, only 20 studies (47.6%) clearly identified the algorithms utilized, while 22 (52.4%) did not specify any algorithm. This observation highlights a potential gap in the implementation of fairness algorithms to address discrimination issues in business processes and process mining.

The specified algorithms include a variety of methods with differing levels of complexity and application scopes. Some algorithms mentioned include classification methods, root cause analysis, tree classifiers [27], Heuristic Algorithm [5], Predictive Policing Algorithms (PPA) [15], Shapley Additive Explanations (SHAP) [40], deep Q-learning [7], and genetic algorithms such as Non-Dominated Genetic Algorithm Sorting II (NSGA-II) [10]. These algorithms address fairness from multiple perspectives, including predictive accuracy, causal analysis, and optimization approaches.

Despite the promising range of algorithms employed, the high percentage of unspecified algorithms raises concerns about the clarity of current literature in this domain. The lack of specification might suggest that fairness is either underexplored or that the methodological rigor in documenting algorithmic approaches is insufficient. There is a need for a more standardized framework or reporting practice where algorithmic choices are explicitly discussed. Such a practice would facilitate reproducibility and provide clearer insights into how fairness is being operationalized within business processes and process mining.

Moreover, there is a noticeable reliance on well-established algorithms like decision trees and heuristic algorithms, which may indicate a trend toward using traditional models for fairness assessment. Additionally, the integration of more sophisticated machine learning algorithms, such as deep Q-learning. This suggests a growing recognition of the importance of adaptive, reinforcement learning-based approaches in achieving fair outcomes.

Further analysis of data mining and machine learning implementation in fairness studies reveals a significant gap in the field. Only 38% of the studies explicitly incorporate data mining or machine learning techniques in their fairness analysis, while 62% do not utilize these advanced analytical methods. This notably low implementation rate suggests that, despite the potential of data mining and machine learning to identify and address fairness issues in business processes, these technologies remain underutilized in current research. Meanwhile, the remaining studies generally implement statistical methods to measure fairness.

The limited adoption of data mining and machine learning approaches may be attributed to several factors. First, the complexity of integrating fairness considerations into automated analysis systems could present technical challenges for researchers. Second, the relative novelty of applying these techniques to fairness assessment in business processes means that established frameworks and best practices are still emerging. This observation aligns with our earlier finding regarding the high percentage of unspecified algorithms, suggesting a broader pattern of hesitancy in adopting sophisticated computational approaches to fairness analysis.

3.4 Challenges and Limitations

A major limitation highlighted is the potential for direct discrimination within process mining analyses, particularly when dealing with sensitive data, as the decisions made by automated systems can accidentally replicate or cause existing biases. Addressing these limitations requires a multi-faceted approach, including both technical and conceptual strategies to ensure that biases are identified and mitigated during the process mining lifecycle [35].

The data highlights key insights into the development tools and event logs used in process mining to ensure fairness. A significant portion of the studies did not specify the process mining tools or event logs used. Specifically, 21.4% of the studies identified PM tools, 16.6% mentioned non-PM tools, while 61.9% did not specify any tools. Similarly, regarding event logs, only 28.57% of the reviewed studies used real-life event logs, 16.6% used simulated event logs, while 54.7% did not specify the type of event log used.

Only 19 studies provided event logs, and 12 of them used real-world data, but none included sensitive attributes such as gender, age, race, or salary [13]. These attributes are crucial for assessing process fairness because potential discrimination can only be detected when outcomes are compared across groups. As current real-world logs contain only generic process information (case ID, timestamp, activity, actor), most studies artificially added sensitive attributes [25], which limits the realism of fairness analysis.

4 Discussion

Our review reveals that there are implicit assumptions about fairness. The findings suggest that fairness in process mining is often implemented at the group or population level rather than the individual level. As shown in Table 2, equality is the most frequently applied distributive justice principle (47.62%), indicating a preference for standardized procedures that treat all participants the same, particularly in governance contexts. This connects to Homans' theory of distributive justice [9] and highlights the tension between standardized procedures and individualized fairness: while uniform rules can promote consistency, they may fail to account for individual circumstances or needs. Although formal procedures (procedural justice) are commonly in place, their application often depends on case-specific contexts. This flexibility can be positive when it allows processes to adapt to individual needs, but it also creates risks of inconsistency or bias if not transparently justified. Therefore, the challenge lies in balancing standardized rules with context-sensitive applications that preserve both fairness and accountability.

A key issue identified in this review is the limited specification of fairness metrics. Table 4 shows that only two studies explicitly define fairness measures such as demographic parity and individual fairness [22]. Nearly half of the studies do not mention any metric at all, raising concerns about the transparency and reproducibility of fairness assessments. While nearly half of the reviewed studies applied machine learning techniques, only a small number (five studies) integrated fairness concepts into process mining settings. None of these implemented fairness measurement as part of the process mining tools. In addition, 61.9% of the studies did not specify the tools used, and only a few employed real-life event logs with sensitive attributes, which limits the applicability of fairness assessments in real-world contexts.

These gaps point to significant opportunities for future research. Efforts should focus on developing fairness-aware algorithms, enriching real-life event logs with sensitive attributes, and integrating fairness into Responsible AI and BPM frameworks. Extending fairness-aware process mining to domains such as healthcare and judicial systems will further strengthen its impact.

5 Conclusion

In conclusion, the studies indicate a recurring issue of insufficient specification and transparency in the literature on fairness in process mining. By analyzing 42 relevant studies, we identified key themes, methodological trends, and challenges in integrating fairness into process mining and business processes. The review also reveals that fairness research is growing in high-impact sectors such as governance, finance, and healthcare. There are opportunities for improvement in terms of transparency regarding tools, data, metrics, and algorithms.

To advance the field, it is essential to clearly define fairness metrics and address the under-utilization of analytical methods in order to improve the documentation of tools and methodologies. Implementing best practices, such as using a balance of real and simulated event logs, standardized conversion methods, and transparent reporting, will establish a strong foundation for effectively applying fairness algorithms in process mining. These insights can contribute to more robust, fair, and replicable research in this growing area.

Overall, fairness in business processes and process mining is not only a technical issue but also a critical aspect of responsible and ethical technological transformation. By outlining the current state of fairness research, this review provides guidance for a more structured and impactful path toward fairness-aware process mining.

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