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Faculty of Business Economics

Master of Management

Master's thesis

Evaluating the Rigor of Process Mining Reporting: Introducing the Process Mining Reporting Excellence (PROMIRE) guideline

Ladonai Ami Koeswandi

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Data Science

SUPERVISOR :
Prof. dr. Niels MARTIN

MENTOR :
Mevrouw An VANTHIENEN

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www.uhasselt.be
Universiteit Hasselt
Campus Hasselt:
Martelarenlaan 42 | 3500 Hasselt
Campus Diepenbeek:
Agoralaan Gebouw D | 3590 Diepenbeek

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Evaluating the Rigor of Process Mining Reporting: Introducing the Process Mining Reporting Excellence (PROMIRE) guideline

Ladonai Ami Koeswandi

Faculty of Business Economics, Hasselt University
Agoralaan gebouw D, 3590 Diepenbeek, Limburg, Belgium

Process mining has emerged as a powerful tool for analyzing event data to optimize organizational processes, yet the field lacks standardized reporting guidelines to ensure transparency, rigor, and reproducibility in case studies. Addressing this gap, this study introduces the PROMIRE guideline (Process Mining Reporting Excellence), a comprehensive 18-item checklist developed by analyzing reporting standards across various disciplines and synthesizing these findings with insights derived from the PM² Methodology. PROMIRE provides structured reporting criteria across all stages of process mining projects, from planning and data extraction to analysis and validation. To evaluate its robustness, a systematic assessment of adherence to PROMIRE was performed in 28 peer-reviewed process mining case studies (2019-2025). Results revealed critical gaps, including underreporting of ethical considerations (4/28 studies) and reproducibility measures (1/28), despite strong adherence to foundational elements like objectives (100%). The guideline's evidence-based structure, validated through both methodological synthesis and empirical evaluation, successfully captures essential reporting elements that are often overlooked in current practice. By bridging domain-specific needs with existing reporting principles, PROMIRE aims to elevate the quality, credibility, and practical impact of process mining research, fostering reproducibility and actionable insights for academia and industry alike.

Keywords - *process mining; case study; reporting guidelines; transparency; reproducibility*

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1 Introduction

Modern organizations operate a variety of business processes, such as complaint handling or order fulfillment, which are increasingly supported by information systems. These systems capture detailed digital traces of process execution, forming the foundation for process mining analysis. The emerging field of process mining analyzes such event data to understand and improve organizational processes, offering valuable insights through structured records of process activities that typically include case identifiers, timestamps, and activity names. This capability has attracted broad research interest from academia and industry alike, driven by both the growing availability of event data and the need for business process optimization in changing environments (Berti, Van Zelst, & Van der Aalst, 2019; Van Der Aalst et al., 2012). By analyzing event logs, process mining techniques help companies gain a deeper understanding of their operational processes, uncover bottlenecks, and enhance overall performance through data-driven refinements (Berti et al., 2019).

Van der Aalst (2022) categorizes the field into six main analytical approaches: (1) process discovery focuses on extracting process models (graphical representations of business processes) from event data; (2) conformance checking compares observed behavior with reference models to detect deviations; (3) performance analysis examines timing and resource utilization to evaluate process efficiency beyond just bottleneck identification; (4) predictive monitoring uses historical data to forecast future process behavior; (5) comparative process mining analyzes differences between process variants across groups of cases (e.g., customer segments) or time periods (e.g., pre/post-intervention); and (6) action-oriented process mining suggests interventions to improve processes. These techniques work synergistically in practice. For instance, conformance checking might reveal that 15% of insurance claims deviate from standard procedures, while performance analysis could show these deviations add an average of 3.2 days to processing times. Such insights enable organizations to make data-driven improvements, for example, an insurer might redesign claim approval workflows for frequent deviation patterns - demonstrating how process mining transforms raw event data into actionable business intelligence (Jans & Eulerich, 2022; Van der Aalst, 2016).

The versatility and applicability of process mining have led to its adoption across various domains, as evidenced by a growing number of case studies published in scientific literature. These studies demonstrate the practical value of process mining across domains such as healthcare (Rojas, Munoz-Gama, Sepúlveda, & Capurro, 2016), manufacturing (Son et al., 2014), and finance (Jans & Eulerich, 2022). However, despite the increasing number of process mining case studies, there is a notable absence of standardized reporting guidelines, structured frameworks that specify what methodological and contextual information should be documented to enable evaluation and replication. Koorn et al. (2021) conducted a systematic literature review comprising 80 process mining case studies, revealing critical documentation gaps: nearly one-third (29%) of studies neither described their evaluation methodology nor clearly stated research goals, despite frequent involvement of domain experts in validations. These reporting gaps, particularly the omission of evaluation protocols and ambiguous study objectives, directly hinder the field's ability to produce reliable, actionable knowledge that can drive both academic progress and practical innovation, highlighting substantial room for improvement in how studies are documented and presented.

In contrast, fields like clinical research and machine learning have put in place some solid reporting guidelines to guarantee transparency and reproducibility. For instance, clinical research has embraced well-established guidelines such as the CONSORT statement (Schulz, Altman, & Moher, 2010) for randomized controlled trials (RCTs) and the TRIPOD guidelines (Collins, Reitsma, Altman, & Moons, 2015) for predictive models. Similarly, machine learning has developed standards like the MINIMAR (Hernandez-Boussard, Bozkurt, Ioannidis, & Shah, 2020) for medical AI reproducibility and the CAIR checklist (Olczak et al., 2021) for clinical AI research. In addition, simulation research is also offering STRESS guidelines (Monks et al., 2019) to improve the reporting quality of simulation studies in different types of simulation studies. These guidelines provide structured reporting requirements, for instance, CONSORT mandates detailed descriptions of trial participant flow, while TRIPOD specifies how prediction models should be validated, enabling critical appraisal and replication of studies. While process mining has developed methodological standards for conducting research, such as the Artifact framework (Jokonowo, Claes, Sarno, & Rochimah, 2018) and Van der Aalst (2016)'s process mining lifecycle, these focus primarily on how to execute studies rather than how to document them. Methodological standards guide research design and execution, whereas reporting guidelines specify what information should be included in publications to allow evaluation and replication. This distinction is crucial because rigorous methodology alone cannot ensure transparency if key details are omitted in reporting. Currently, process mining lacks such dedicated reporting guidelines, creating a gap that hinders consistent documentation and limits the field's ability to build cumulative knowledge from case study findings.

To address this gap, this paper introduces the PROMIRE (Process Mining Reporting Excellence) guideline, a reporting guideline that adapts cross-domain guidelines to the specific needs of process mining case studies. Developed by aligning the PM² methodology's structured project stages (planning, extraction, data processing, mining & analysis, evaluation, and process improvement) (Van Eck, Lu, Leemans, & Van Der Aalst, 2015) with established reporting guidelines from other fields, PROMIRE was tested through systematic application to existing process mining case studies. The guideline provides researchers with a practical 18-item checklist to support more rigorous and transparent reporting of process mining studies, addressing key aspects from context background to data provenance to validation methods while allowing flexibility for different research contexts. By improving the completeness and consistency of published work, PROMIRE aims to increase the transparency and comparability of process mining research. To demonstrate its applicability, the guideline was tested by assessing reporting quality in 28 process mining case studies between 2019 and 2025, where the papers were extracted from the Web of Science database in March 2025, revealing both current reporting gaps and opportunities for improvement.

The remainder of this paper is structured as follows: Section 2 reviews existing reporting standards from related fields and positions the PM² methodology as a bridging framework that connects these cross-disciplinary reporting guidelines with process mining's unique requirements. Section 3 details the methodology to develop PROMIRE guideline. Section 4 presents the guidelines, explaining the rationale for each item. Section 5 presents the results of the adherence evaluation to published process mining case studies, including quantitative metrics and qualitative insights. Section 6 discusses implications for research and practice before concluding in Section 7.

2 Related Work

Establishing reporting guidelines for process mining case studies draws upon two distinct yet interrelated knowledge domains. First, established reporting guidelines from other scientific disciplines demonstrate systematic approaches to research transparency, offering adaptable frameworks for methodological disclosure in developing process mining's own reporting guideline. Second, process mining's methodological literature, particularly the PM² methodology, provides critical insights into the essential elements that should be considered in the process mining project life-cycle where it serves as the foundation of content in process mining reporting guidelines. This dual perspective enables the derivation of reporting guidelines that satisfy both general scientific standards and process mining's particular analytical needs.

2.1 Cross-domain reporting guidelines

The development and application of rigorous reporting guidelines in other scientific fields offer valuable insights for advancing process mining research, particularly for case study reporting. This review examines both the development approaches (e.g., a literature review, consensus building) and final products (e.g., checklists, flow diagrams) of established guidelines in clinical research, artificial intelligence, and simulation studies, focusing on selected representative examples rather than an exhaustive catalog. These examples were chosen for their methodological rigor, widespread adoption, and relevance to process mining's interdisciplinary nature.

2.1.1 Clinical research: CONSORT and TRIPOD

In the realm of clinical research, standardized reporting guidelines have been developed to enhance transparency and reproducibility. The CONSORT 2010 Statement (Consolidated Standards of Reporting Trials) (Schulz et al., 2010) serves as a pivotal guideline for reporting parallel group randomized trials, emphasizing the need for clear and comprehensive documentation to mitigate bias and improve the reliability of trial outcomes. Developed through a rigorous consensus process, the guidelines include a 25-item checklist and a participant flow diagram to ensure methodological details, such as randomization, blinding, and statistical analysis, are thoroughly reported. While CONSORT has significantly improved trial reporting, its applicability is primarily limited to parallel group designs, and adherence remains inconsistent across journals.

Similarly, the TRIPOD Statement (Transparent Reporting of a Multivariable Prediction Model for

Individual Prognosis or Diagnosis) (Collins et al., 2015) provides clinical researchers with essential guidance for reporting prediction models, offering a 22-item checklist to standardize the documentation of model development, validation, and performance metrics. Like CONSORT, TRIPOD focuses on reporting quality rather than methodological rigor and faces challenges in widespread adoption. Both guidelines serve as essential tools for researchers, peer reviewers, and clinicians, facilitating critical appraisal and informed decision-making. While these guidelines were originally developed for clinical and diagnostic research, their emphasis on structured reporting, avoidance of bias, and reproducibility offers valuable insights to ensure comprehensive and standardized reporting in process mining research. For instance, process mining studies involving interventions (e.g., evaluating process improvements) could benefit from CONSORT's structured approach to trial reporting, while predictive process mining aligns with TRIPOD's focus on model transparency.

2.1.2 Artificial Intelligence: MINIMAR and CAIR

The rapid adoption of artificial intelligence (AI) across the healthcare sector and other industries has led to the development of new reporting guidelines. Most notable among them are the MINIMAR short for MINimum Information for Medical AI Reporting and the CAIR checklist as in Clinical AI Research checklist. MINIMAR was designed to improve the reliability of medical AI studies by establishing baseline reporting requirements to: (1) clarify prediction tasks and intended clinical use, (2) define target patient populations, and (3) identify potential biases that may affect model generalizability. Developed specifically to standardize medical AI reporting, this framework emphasizes documentation of the clinical context, data provenance, and validation approaches - elements equally crucial for healthcare process mining studies where understanding event log demographics, process context, and algorithmic limitations determines real-world applicability (Hernandez-Boussard et al., 2020). For example, process mining studies could adopt MINIMAR's approach to reporting data demographics and model performance.

The CAIR Checklist provides a guideline for reporting clinical AI research, focusing on documentation of algorithms, hyperparameters, and software tools. Additionally, CAIR mandates reporting of ethical considerations including data privacy protections and bias mitigation strategies (Olczak et al., 2021). CAIR emphasizes algorithmic transparency and ethical considerations, which are equally important for process mining. For example, process mining case studies could require researchers to specify the process mining algorithm used (e.g., Inductive Miner) and its parameter settings (e.g., noise threshold).

While both guidelines originate from medical AI, their principles extend to other domains. MINIMAR's emphasis on use-case specification applies equally to industrial process mining applications, just as CAIR's technical reporting requirements are universal across AI-driven analytics. Their adaptation across clinical and non-clinical contexts demonstrates how domain-inspired guidelines can inform process mining reporting guidelines while allowing necessary flexibility for different application areas.

2.1.3 Simulation studies: STRESS guidelines

Simulation research offers methodological parallels to process mining through the STRESS (Strengthening the Reporting of Empirical Simulation Studies) guidelines, which were specifically developed to improve the reporting quality of simulation studies in different types of simulation studies (Monks et al., 2019). These guidelines emphasize comprehensive documentation of three critical aspects particularly relevant to process mining: model assumptions that underpin the simulation, initialization parameters that define starting conditions, and runtime conditions that affect execution. This focus on technical transparency is able to inform process mining applications involving conformance checking and predictive monitoring, where similar requirements exist for documenting process model assumptions, event log preprocessing parameters, and analysis runtime environments. The STRESS guidelines' structured reporting of study objectives, model design rationale, and implementation details provides a particularly valuable template for process mining case studies, demonstrating how standardized documentation can support both methodological rigor and reproducibility in data-driven process analysis.

2.2 PM² Methodology: Foundations for process mining project

While those cross-domain guidelines establish core reporting principles, process mining projects require careful methodological structuring due to their iterative nature and reliance on intermediate artifacts such as event logs and process models. The PM² methodology (Van Eck et al., 2015) provides a structured approach through six defined stages: (1) planning, where research questions and project scope are established; (2) extraction, focusing on event log acquisition; (3) data processing, involving quality checks and transformations; (4) mining and analysis, where process models are discovered and analyzed; (5) evaluation, validating results with domain experts; and (6) process improvement, implementing changes based on findings.

The IBM case study implementation of PM² (Van Eck et al., 2015) demonstrated PM²'s practical application, revealing several documentation-sensitive aspects: timestamp inconsistencies requiring complete event log re-extraction highlighted the need for data quality reporting; varying outcomes from different ProM (short for Process Mining framework, an open source framework for process mining algorithms) plugin configurations emphasized the importance of tool documentation; and domain expert validations underscored the value of recording verification processes. These insights demonstrate how PM²'s execution framework naturally identifies critical artifacts that should be documented, though the methodology itself focuses on project execution rather than reporting standards.

While PM² does not explicitly define reporting requirements, its stage-based approach provides valuable insights into what information matters in process mining projects. For instance, its emphasis on documenting case notion selection - the fundamental decision about what constitutes a single instance of a process (e.g., treating each customer order as a separate case in an order fulfillment process) - during event log creation corresponds to CONSORT's participant flow reporting, and its validation stages go beyond TRIPOD's model validation by incorporating domain expert verification. This makes PM² particularly useful for understanding what elements should be considered when developing process mining reporting guidelines, while recognizing that actual reporting standards require additional specification beyond methodological execution.

3 Methodology

This study followed a methodical three-stage process to develop and evaluate the PROMIRE guideline for process mining case studies. First, a comprehensive analysis of existing reporting standards from related disciplines identified transferable principles and best practices. Second, these cross-domain insights were systematically integrated with process mining-specific requirements to construct the PROMIRE guideline. Third, the guideline's applicability was evaluated through an assessment of reporting practices in existing case studies. Together, these stages ensured the guideline's development was both theoretically grounded in established reporting principles and practically validated against current process mining research.

3.1 Review of existing reporting guidelines

The development of the PROMIRE guideline began with a comprehensive review of existing reporting guidelines, informed by methodological principles from Arksey and O'Malley (2005). Key research questions focused on how existing reporting guidelines were developed and tested, and what best practices could be adapted for process mining case studies. Peer-reviewed studies describing the development or validation of reporting guidelines were identified through searches in Web of Science, Scopus, and the EQUATOR Network using the query ("reporting guidelines" OR "reporting standards") AND ("development" OR "validation"). Five existing reporting standards in related fields like clinical research, artificial intelligence (AI), and data science were selected to inform PROMIRE's development: CONSORT for clinical trials (Schulz et al., 2010), TRIPOD for prediction models (Collins et al., 2015), MINIMAR for medical AI (Hernandez-Boussard et al., 2020), CAIR for clinical AI research (Olczak et al., 2021), and STRESS for simulation studies (Monks et al., 2019). These frameworks were analyzed on two aspects: (a) methodological approaches used in guideline development, and (b) common contents or topics that were considered important by experts in their respective domains.

3.2 Construction of the PROMIRE guideline

The development of the PROMIRE guideline emerged from a synthesis of cross-disciplinary reporting standards and process mining methodology. Building systematically upon five established frameworks (CONSORT, TRIPOD, CAIR, MINIMAR, and STRESS), the guideline construction followed a content-mapping methodology that identified essential reporting elements through comparative analysis. This approach examined each source guideline to extract common requirements - specifically, CONSORT's structured study design principles informed PROMIRE's validation reporting, TRIPOD's model transparency requirements guided algorithm documentation, and CAIR's AI-specific details enhanced methodological reproducibility. MINIMAR's focus on data biases and STRESS's stakeholder engagement criteria further shaped PROMIRE's data quality and contextual reporting items. These cross-disciplinary elements were subsequently integrated with the PM^2 methodology's six-stage framework (Van Eck et al., 2015), creating a tailored reporting standard that addresses both universal research principles and process mining's project requirements. PM^2's six-stage framework revealed critical reporting needs specific to process mining projects, particularly in documenting event log characteristics during the extraction stage, algorithm configurations during mining and analysis, and domain expert validation methods during evaluation. This combined analysis of existing reporting standards and process mining-specific requirements resulted in the initial PROMIRE guideline.

3.3 Evaluation of guideline adherence

The evaluation of PROMIRE guideline adherence involved study selection, quality assessment, and synthesis of findings. For study selection, the Web of Science database was selected as the primary resource for sourcing process mining case studies. This choice was driven by the database's extensive coverage across various academic disciplines, adherence to rigorous quality standards, advanced citation analysis tools, and its efficient search functionalities (Birkle, Pendlebury, Schnell, & Adams, 2020). In March 2025, a targeted search query was executed using the terms ("process mining" AND "case study") NOT ("algorithm" OR "framework") in article titles without additional filters. This query yielded a preliminary pool of 205 potential studies for further scrutiny.

First, time boundaries were defined through a process of iterative testing (Kitchenham, 2004). The 2019–2025 timeframe was chosen as this period reflects the phase of growing maturity in process mining applications, characterized by more structured methodologies, and increased adoption in industry (Van der Aalst, 2022). Next, the selection process applied stringent inclusion criteria to ensure methodological consistency: (1) peer-reviewed articles in English, (2) empirical process mining case studies using real-world datasets, (3) with "process mining" and "case study" clearly indicated in the title or abstract. Theoretical papers, algorithm-focused studies (even those using real data for demonstration), and non-peer-reviewed works were excluded. After removing duplicates and applying these criteria, a final set of 28 case studies was obtained for analysis.

Each of the 28 selected case studies was evaluated against the PROMIRE guideline using a binary scoring system (reported/not reported) for each checklist item. The binary scoring was chosen for its clarity in identifying missing elements in process mining project reporting. For instance, studies received credit for "Data Provenance" if they explicitly described their event log sources and extraction time periods, while "Parameter Settings" required documentation of specific configurations like noise thresholds or fitness criteria.

The analysis combined quantitative and qualitative methods. Quantitative assessment measured adherence rates across all studies, while qualitative examination identified recurring patterns in reporting practices through iterative review of study sections and comparison against PROMIRE guideline. This dual approach allowed us to identify both the prevalence and nature of reporting deficiencies in current process mining case studies.

4 Result

The development of PROMIRE integrated insights from two complementary perspectives: established reporting standards from related disciplines (CONSORT, TRIPOD, CAIR, MINIMAR, and STRESS) and process mining's methodological requirements (PM² Methodology). The resulting 18-item checklist addresses the critical element of process mining research: ensuring transparency in data provenance (e.g., event log sourcing), methodological rigor (e.g., tool configurations), and practical relevance (e.g., stakeholder-driven validation). By adapting these cross-disciplinary standards, PROMIRE provides a tailored guideline to systematically assess and improve reporting quality in process mining case studies, emphasizing reproducibility and actionable insights.

4.1 Synthesis of existing guidelines and PM² Methodology

The review of five established reporting guidelines revealed consistent methodological rigor in their development processes, all demonstrating the critical role of domain expertise in creating authoritative standards (see Table 1). CONSORT (Schulz et al., 2010) used formal Delphi techniques with panels of clinical trial experts to achieve consensus on its checklist items, establishing a benchmark for evidence-based guideline development. TRIPOD (Collins et al., 2015) extended this approach by combining systematic reviews of prediction model studies with multidisciplinary expert input from statisticians, clinicians, and methodologists. The AI guidelines showed similar patterns: MINIMAR (Hernandez-Boussard et al., 2020) incorporated iterative feedback from both AI researchers and practicing clinicians, while CAIR (Olczak et al., 2021) implemented a rigorous three-round validation process involving 42 domain experts from clinical AI research and practice. STRESS (Monks et al., 2019) uniquely blended systematic literature analysis with hands-on simulation community workshops.

These development approaches collectively demonstrate that authoritative reporting guidelines require both evidence-based methods (systematic reviews, Delphi techniques) and substantive domain expert engagement throughout development. While PROMIRE's scope did not permit full replication of these intensive processes, their fundamental lesson - that credible reporting standards must balance methodological rigor with field-specific expertise - directly informed its approach. This is reflected in PROMIRE's design, where each checklist item was validated against both cross-domain reporting principles and established process mining methodologies (Van der Aalst, 2016), ensuring the guideline remains grounded in the field's actual needs and practices.

4.1.1 Common content themes across existing guidelines

The guideline analysis identified three recurring content priorities that transcended disciplinary boundaries. First, contextual transparency was emphasized by all five guidelines, though with domain-specific implementations: CONSORT and TRIPOD require detailed background about clinical settings, while CAIR and MINIMAR focus on AI system deployment contexts (present in both AI standards). Second, data quality documentation appeared universally, with TRIPOD and MINIMAR mandating missing data reporting, and STRESS requiring simulation input verification. Third, validation procedures were consistently required, though their forms varied from statistical testing (TRIPOD) to domain expert review (CAIR).

4.1.2 Integration with PM² Methodology

The PM² methodology acts as the bridge between process mining and cross-domain reporting guidelines, ensuring that PROMIRE is both domain-agnostic and methodologically sound. As shown in Table 1, readers may refer to the table when reporting a process mining case study, as it provides a structured guideline for reporting key elements across all stages of the project. Each row in the table corresponds to a specific content-related item, mapped to the PM² stages (e.g., Planning, Extraction and Data Processing, Mining and Analysis), and includes an example and relevant guideline references. For instance, the "Background" item (No. 3) was included in the Planning stage, reflecting both CONSORT/TRIPOD/CAIR's emphasis on context and PM²'s initial stakeholder alignment phase. "Data Quality" (No. 6) appears in Extraction and Data Processing, adapting TRIPOD and MINIMAR's standards to PM²'s artifact verification needs. Notably, some requirements like "Parameter Settings" (No. 11) combined CAIR's technical specificity with PM²'s Mining stage demands, demonstrating how domain-specific needs can augment universal principles. This approach ensures that each item in the PROMIRE guideline is justified by both cross-domain consensus and its relevance to process mining workflows.

4.2 Construction of the PROMIRE guideline

To enhance usability, the PROMIRE guideline is organized around content-related headers rather than traditional paper sections. This structure reflects the dynamic nature of process mining case studies, where information may be scattered across multiple sections (e.g., methods, results, discussion). Table 1 presents the complete PROMIRE reporting checklist, designed to aid researchers in documenting their process mining case studies. Its structure is based on four key design principles. First, it aligns with the PM² project lifecycle, ensuring that researchers can effectively navigate through each phase of their projects. Second, it integrates cross-domain reporting standards, allowing for a more comprehensive approach to documentation. Third, the checklist includes practical implementation examples that help illustrate each requirement. Finally, it explicitly sources each requirement, adding to the checklist's credibility and utility.

The first column of the table, labeled PM² Stage, anchors each checklist item to one of the six phases outlined in the PM² methodology. For instance, planning items such as Background provide essential context for the study, while elements related to Extraction and Data Processing, like Data Quality, address the characteristics of event logs. As the checklist moves into the Mining and Analysis requirements, it emphasizes technical execution with items such as Parameter Settings. Evaluation and Improvement sections focus on capturing validation and reporting the impact of the findings.

In the second column, items are classified by their thematic focus. This categorization includes Ethical Considerations, which emphasize the importance of privacy protocols, and Data Provenance, which highlights the significance of sourcing event logs. Additionally, the Model Representation item underscores the standards required for effective visualization. The third column offers a numbered reference system, which aids in cross-referencing the checklist items clearly within manuscripts. Meanwhile, the fourth column specifies the exact reporting requirements with action-oriented language. This includes directive verbs like "Identify," "Provide," and "Document," which contribute to consistency and clarity. Furthermore, technical specifics, such as mentioning the "noise threshold" in the Parameter Settings, ensure that the criteria are precise and understandable.

In the fifth column, the checklist provides concrete implementations of the requirements. For example, it references a hospital discharge case to demonstrate healthcare applications or discusses an SAP ERP system to illustrate enterprise contexts. Python scripts are also mentioned as examples of reproducibility measures, adding practical relevance to the documentation process. Lastly, the sixth column traces the provenance of each item, linking them to established guidelines. Clinical standards like CONSORT and TRIPOD prevail in the Planning items, while AI guidelines such as CAIR and MINIMAR inform technical reporting. Moreover, simulation research standards like STRESS contribute to documenting practical impact.

Table 1: PROMIRE guideline

PM² stage	Content-related	Item no	Checklist item	Example	Guideline references
	Title				
		1	Identify the report as an example of process mining applied within a specific case study field.	Optimizing Patient Discharge Workflows at XYZ Hospital: A Process Mining Case Study Using Event Log Analysis.	CAIR, CONSORT, and TRIPOD
	Abstract				
		2	Provide a concise summary of the study, state the purpose of the analysis using process mining, and highlight the real-world impact of the study to show its importance and relevance.	This study applied process mining to analyze delays in patient discharge processes at XYZ Hospital. Using 8,245 discharge event logs from 2022–2023, we discovered 27% of cases exceeded recommended discharge timeframes, primarily due to medication reconciliation bottlenecks (identified via ProM's Performance Spectrum Miner). Domain experts validated these findings through three iterative workshops,...	CAIR, CONSORT, and TRIPOD
Planning					
	Background	3	Describe the organization and process being studied and mention the role of stakeholders.	This study was conducted at XYZ Hospital, focusing on patient discharge. Domain experts from the hospital were involved in validating the results.	CAIR, CONSORT, and TRIPOD
	Objectives	4	Articulate the specific goals and anticipated outcomes of the process mining analysis in a clear and detailed manner.	The goal is to increase adherence to discharge protocols.	CAIR, CONSORT, and TRIPOD

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PM² stage	Content-related	Item no	Checklist item	Example	Guideline references
	Ethical Considerations	5	Ensure the protection of privacy and uphold the principles of confidentiality. Mention whether or not ethical approval was granted.	[1]Patient identifiers were removed from the event logs to ensure privacy. [2]The research project was reviewed by the ethical committee at Hospital XYZ to ensure it adheres to ethical guidelines and principles.	CAIR and TRIPOD
Extraction and Data Processing					
	Data Provenance	6	Provide a detailed identification of the origin or source from which the event log is generated.	Event logs were extracted from the SAP ERP system at XYZ Hospital.	TRIPOD and MINIMAR
	Data Quality	7	Transparently report all identified data quality issues and their handling procedures.	The event log contained 10% missing timestamps, which were imputed using linear interpolation based on adjacent events within the same case.	TRIPOD and MINIMAR
	Event Log Structure	8	Provide a comprehensive overview of the key attributes associated with the event log.	The log includes case ID, activity name, timestamp, and resource info.	TRIPOD and MINIMAR
	Data Preprocessing	9	Document all critical preprocessing steps applied to the event log, ensuring reproducibility.	Events with missing case IDs were removed.	TRIPOD and MINIMAR
Mining and Analysis					
	Process Mining Technique and Tool	10	Indicate the specific technique and algorithm employed along with the software tool utilized for its implementation in X context.	Process discovery was performed using the Inductive Miner algorithm using the Disco tool.	CAIR and CONSORT
	Parameter Settings	11	Thoroughly catalog the specifications and settings of the algorithm.	A noise threshold of 0.2 was applied to filter out infrequent paths.	CAIR and CONSORT
	Model Representation	12	Explain how the visualization of the process model is represented.	The discovered process model was represented as a BPMN diagram.	TRIPOD and MINIMAR

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PM² stage	Content-related	Item no	Checklist item	Example	Guideline references
Evaluation					
	Validation	13	Provide a detailed explanation of the various methods and processes employed to validate the results obtained.	The process model was validated by comparing it with standard procedures.	TRIPOD and MINIMAR
	Performance Metrics	14	Report all evaluation metrics used to assess the quality and effectiveness of process mining outputs.	The model achieved a fitness score of 0.92 and a precision score of 0.85.	TRIPOD
	Process Goals	15	Reiterate the objectives and how they were achieved.	[Initial Goal]: Understand general discharge delays at XYZ Hospital. [Refined Goal]: Quantify time delays between discharge order entry and patient exit, focusing on medication reconciliation steps for general medicine patients.	STRESS
	Limitations	16	Recognize and reflect on the limitations or inadequacies present within the scope of the study.	The study was limited by the availability of only one year of event log data.	CAIR, CONSORT, and TRIPOD
Improvement					
	Practical Implications	17	Discuss the real-world impact of the findings and emphasize the wider significance of the results and their implications for future research.	The study's findings informed two operational changes at XYZ Hospital: [1] new pharmacist-nurse handoff protocol during discharge, reducing average reconciliation time by 42 minutes ($p < 0.01$). [2] Revised EHR discharge order templates incorporating process mining-identified bottleneck patterns.	STRESS and TRIPOD
	Reproducibility	18	Outline the measures implemented to guarantee reproducibility.	The event log and Python scripts used for analysis are available through Dataverse, DataHub or institutional repository.	STRESS

Overall, the horizontal organization of the table reflects the sequential workflow of the PM² methodology, while a vertical reading reveals how cross-domain standards have been adapted. For instance, TRIPOD's model validation, which is rooted in clinical research, is transformed into the Validation item for process mining within the Evaluation stage of PM². This dual-axis structure ensures that the checklist covers all necessary aspects comprehensively, while specifically addressing the unique requirements of different fields.

5 Adherence of PM case studies to PROMIRE guideline

A systematic evaluation of 28 process mining case studies against the PROMIRE guideline revealed significant patterns in reporting quality (see Figure 1). While foundational elements like titles, abstracts, and objectives (Items 1-4) were universally reported (100% adherence), critical gaps persisted in ethical considerations (Item 5, 4/28 studies) and reproducibility (Item 18, 1/28). The analysis showed particularly concerning omissions in healthcare studies - for instance, Article 2 (Garcia, Meincheim, Filho, Santos, & Scalabrin, 2019) agility case study of multinational business processes completely lacked ethical disclosures despite handling sensitive operational data, while Article 27 (Valero-Ramon, Fernandez-Llatas, Collantes, Valdivieso, & Traver, 2024) prostate cancer research stood out as a positive example with explicit ethics approvals. This disparity highlights an inconsistent approach to ethical reporting even within sensitive domains.

The Extraction and Data Processing stage showed uneven adherence. While data provenance (Item 6, 27/28) and event log structure (Item 8, 25/28) were mostly documented, Article 23 (Claus et al., 2024) omitted the latter, and Article 3's (Chiu & Jans, 2019) internal control study built upon (Jans, Alles, & Vasarhelyi, 2014) led to missing data preprocessing details (Item 9), a recurring issue in 6 studies (e.g., Articles 12 (Nai, Sulis, Marengo, Vinai, & Capecchi, 2023), 18 (Rott et al., 2023)). Article 10 COVID-19 analysis (Pegoraro et al., 2022) deliberately bypassed data quality reporting (Item 7) due to 98% conformance fitness, a justifiable but exceptional case that underscores the need for context-aware reporting standards. Meanwhile, Articles 7 (Hachicha, Ghorbel, Champagnat, Zayani, & Amous, 2021) and 21 (Kretzschmann, Park, Berti, & Van der Aalst, 2024) emphasized data quality in hospital and object-centric studies, respectively, demonstrating domain-specific adaptations.

Mining and Analysis transparency varied significantly: though most studies specified tools (Item 10, 26/28 adherence), Article 12's vague tool descriptions and Article 8's omission of performance metrics

(Hobeck, Klinkmüller, Bandara, Weber, & Aalst, 2021) (Item 14) were emblematic of broader gaps. Parameter settings (Item 11) remained severely underreported (8/28), with Articles 16 (Butt et al., 2023) and 21 attributing this to algorithmic diversity or object-centric approaches. The PM²-aligned studies (Article 6 (Kurniati, Hall, Hogg, & Johnson, 2021); Article 15 (Hobeck, Pufahl, & Weber, 2023)) demonstrated near-complete compliance, achieving 94% average adherence and validating the methodology's effectiveness.

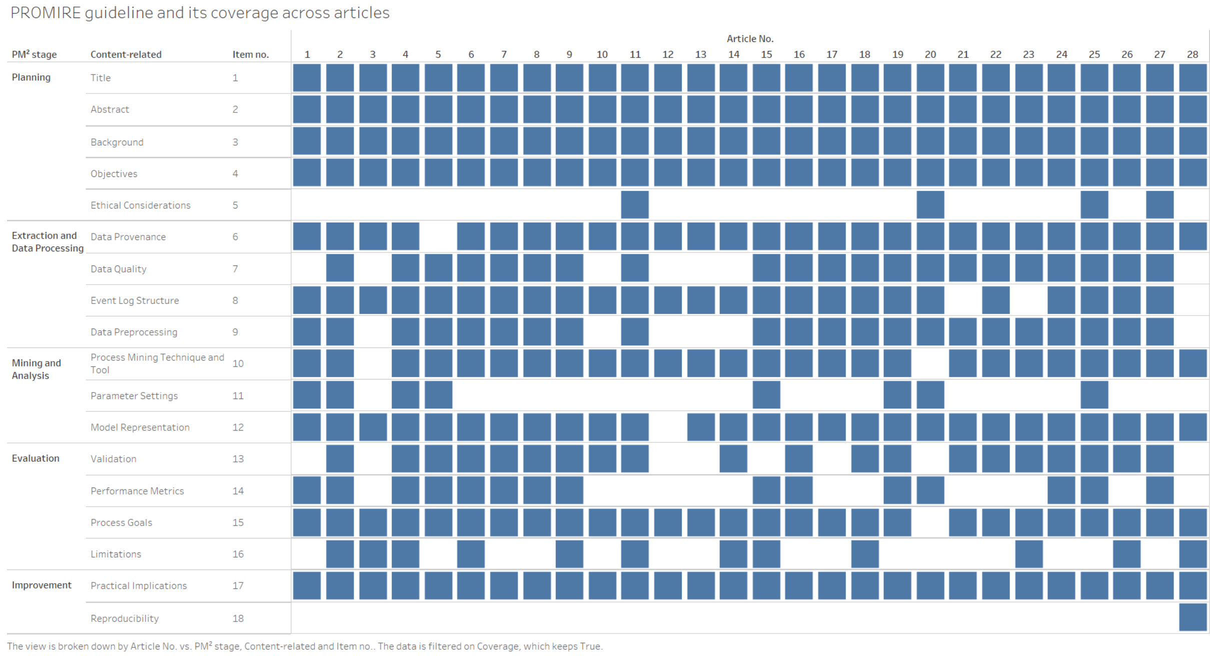

Figure 1: PROMIRE Guideline and its coverage across articles

Model representation favored practical outputs (Petri nets, heuristic miner nets) over methodological transparency, with Article 2's multinational agility study typifying this trend; it validated process improvements but provided no reproducibility mechanisms due to corporate data restrictions. Article 28's DevOps research (Nogueira & Zenha-Rela, 2024) stood out by making GitLab datasets publicly available (Item 18), contrasting with Article 19 (Zhou, Armas-CerVantes, Bozorgi, Otte, & Polyvyanyy, 2024) otherwise rigorous bioprocess manufacturing analysis which missed this opportunity. Evaluation-stage reporting was similarly inconsistent: while Article 5's hospital-DES integration (Tamburis & Esposito, 2020) showed robust validation (Item 13), Articles 13 (Sulis, 2023) and 17 (Velasquez, Anani, Munoz-Gama, & Pascual, 2023) used simulation-generated event logs without deep technical scrutiny, and Article 24's lack of limitations discussion (Item 16) obscured result reliability (Di Federico, Fernández-Llatas, Ahmadi, Shirali, & Burattin, 2024).

The analysis revealed three particularly problematic areas: ethical reporting (absent in 24/28 studies), parameter documentation (missing in 20/28), and reproducibility measures (only Article 28). These gaps persist despite available solutions - for instance, Article 11 (Delgado & Calegari, 2022) e-government study demonstrated how to balance privacy concerns with transparency by clearly documenting anonymization procedures. The PM²-aligned cases (Article 6, 8, 15) prove comprehensive reporting is achievable, with their structured approach yielding 94% average adherence versus 68% in non-PM² studies.

6 Discussion

This study developed and validated the PROMIRE guideline through a dual approach: (1) synthesizing cross-disciplinary reporting standards with PM² methodology to create a tailored checklist, and (2) systematically evaluating its applicability across 28 process mining case studies. The results demonstrate that while foundational elements (e.g., objectives, model representations) are consistently reported, critical gaps in ethical considerations, reproducibility, and technical transparency persist, revealing both the guideline's utility and opportunities for refinement.

The synthesis of five established reporting standards (CONSORT, TRIPOD, CAIR, MINIMAR, STRESS) with PM²'s methodology yielded three key design principles for PROMIRE. First, the guideline's stage-based structure (Planning to Improvement) mirrors PM²'s project lifecycle while incorporating cross-domain requirements - for example, merging TRIPOD's model validation standards (Collins et al., 2015) with PM²'s Diagnose stage need for domain expert verification. Second, content-related headers accommodate process mining's interdisciplinary nature by decoupling reporting items from rigid paper sections, allowing healthcare studies to document ethical protocols differently than manufacturing applications while maintaining comparability. Third, the explicit sourcing of each item (Table 1, Column 6) ensures transparency about adaptations, such as how CAIR's algorithm documentation (Olczak et al., 2021) became PROMIRE's "Parameter Settings" (Item 11) through PM²'s Mining stage requirements. This development approach balances methodological rigor with practical flexibility, though future iterations could benefit from formal Delphi studies with process mining experts to further validate item weighting.

The evaluation of process mining case studies through the PROMIRE guideline reveals both systemic gaps and opportunities for methodological refinement. A key contribution of PROMIRE is its organization around content-related headers rather than traditional paper sections, which directly addresses the fragmented nature of current reporting practices. For instance, while the "Background" content header captures essential contextual information (Item 3: organizational and process details), our analysis found this information scattered across introductions, methodologies, and even case study appendices, a variability that complicates cross-study comparison. This structural flexibility acknowledges real-world reporting diversity (e.g., Article 2's multinational context appearing in a dedicated "Case Environment" section) while providing clear anchors for essential information. However, the need for such adaptation underscores a broader challenge: the absence of established conventions for structuring process mining case study reports, as opposed to research methodologies themselves.

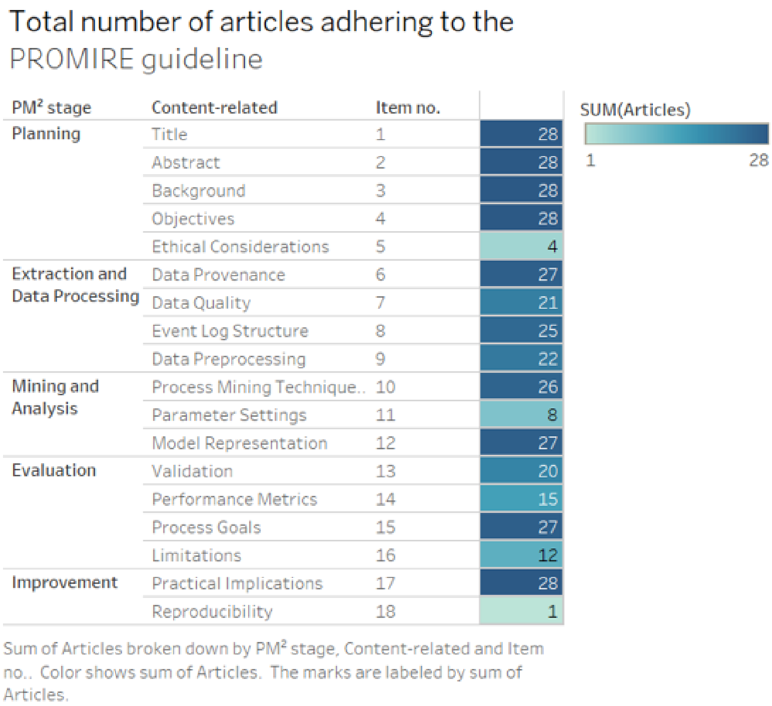

Figure 2: Total Number of Articles Adhering to the PROMIRE Guideline

The near-total absence of ethical considerations (4/28 studies) and reproducibility measures (1/28) underscores a critical blind spot in the field, particularly in sensitive domains like healthcare (see Figure 2). This aligns with external critiques (e.g., Bade, Vollenberg, Koch, Koch, and Coners (2022)) highlighting privacy risks in process mining, warnings about privacy risks in process mining, and suggesting ethical oversight persists despite available solutions (e.g., anonymization protocols). Second, technical transparency gaps—particularly in parameter settings (missing in 20 studies) and reproducibility measures (absent in 27 studies), limit methodological scrutiny. While some omissions were justifiable (e.g., Pegoraro et al. (2022)'s COVID-19 study omitted data quality metrics due to 98% conformance fitness), most lacked a clear rationale. Third, experimental applications (e.g., Zhou et al. (2024)'s bioprocess study) expanded PM's domain reach but frequently prioritized novel insights over technical documentation, potentially hindering replication.

These findings suggest current reporting practices may emphasize actionable outcomes at the expense of methodological rigor, a pattern mirroring early challenges in clinical AI before MINIMAR's adoption (Hernandez-Boussard et al., 2020). However, PM²-aligned studies like Kurniati et al. (2021) and Hobeck et al. (2023) demonstrated that comprehensive reporting is achievable, achieving 94% average adherence versus 68% in non-PM² studies. Their success highlights how structured methodologies can elevate transparency without stifling innovation.

7 Limitations and Future Directions

The evaluation highlights a recurring tension in process mining research between methodological rigor and exploratory innovation. While experimental applications in emerging domains demonstrate the field's expanding applicability, they frequently sacrifice technical documentation of limitations and reproducibility in favor of domain-specific insights. PROMIRE represents an initial attempt to develop standardized reporting guidelines to enhance case study quality, proposing mandatory core transparency requirements while allowing flexibility for supplemental technical details. However, several limitations of this approach must be acknowledged.

First, PROMIRE's current framework may not fully capture the diversity of all process mining applications. The guideline was developed primarily through analysis of existing case studies (2019-2025), which may not anticipate future methodological innovations or novel application domains. Second, the binary (reported/not reported) scoring system, while straightforward, may oversimplify the quality assessment of reported items. A study might briefly mention ethical considerations without substantive discussion, yet still receive the same credit as one providing detailed documentation. Third, the guideline's effectiveness depends on voluntary adoption, and without formal validation through longitudinal studies, its actual impact on reporting quality remains theoretical.

The analysis of modeling approaches reveals further challenges. While PROMIRE identifies opportunities for standardizing reporting of common techniques, its domain-specific supplements remain hypothetical. The development of these supplements would require extensive collaboration with domain experts - a resource-intensive process not yet undertaken. Additionally, the guideline currently lacks mechanisms to address evolving technical challenges, such as reporting requirements for object-centric or streaming process mining approaches that are gaining prominence.

PROMIRE's phased structure successfully accommodates methodological diversity, but this flexibility introduces its own limitations. The scoring system's ability to recognize excellence across different research phases depends on subjective weighting decisions that require further refinement through community input. Moreover, the guideline's current form may inadvertently privilege certain methodologies (like PM²) over others, despite efforts to be inclusive.

As an initial framework, PROMIRE's most significant limitation is its unproven efficacy. While it identifies reporting gaps and proposes solutions, actual improvement in case study quality will depend on widespread adoption and continuous refinement by the process mining community. Future work should focus on validating the guideline through controlled implementation studies and developing governance structures for its ongoing evolution.

8 Conclusion

This study has systematically addressed the critical gap in reporting standards for process mining case studies through the development and evaluation of the PROMIRE guideline. By synthesizing cross-disciplinary frameworks (CONSORT, TRIPOD, MINIMAR, CAIR, STRESS) with the PM² methodology, PROMIRE establishes a tailored 18-item checklist that balances methodological rigor with practical flexibility. The assessment of 28 case studies revealed consistent documentation of foundational elements like objectives (100% adherence) and model representations (93%), but significant shortcomings in ethical considerations (14%) and reproducibility measures (4%), particularly in sensitive domains such as healthcare. These findings underscore a disciplinary blind spot that risks undermining the credibility and translational potential of process mining research.

PROMIRE represents an important first step toward standardized process mining reporting, now made available to the research community as a living document to be used, tested, and adapted as needed. The guideline is not posited as a prescriptive standard, but as: (1) a practical tool for researchers seeking to improve their reporting practices, (2) a starting point for community-led refinements, and (3) a foundation for future validation studies. Looking forward, the implementation of PROMIRE presents an opportunity to transform process mining into a discipline where methodological diversity and scientific transparency reinforce rather than contradict each other. The next critical steps involve engaging the broader research community through collaborations with organizations like the IEEE Task Force on

Process Mining to refine scoring priorities, conducting longitudinal studies to measure the guideline's impact on study reproducibility, and establishing mechanisms for periodic updates to address emerging techniques and applications. By building on the foundation established in this work, the process mining community can develop reporting norms that not only meet current needs but also evolve with the field's growth, ensuring that future research maintains both its practical relevance and scientific integrity. Ultimately, PROMIRE represents more than just a reporting guideline as it serves as a catalyst for elevating process mining to its full potential as a rigorous, transparent, and impactful discipline.

References

Arksey, H., & O'Malley, L. (2005). Scoping studies: towards a methodological framework. *International Journal of Social Research Methodology*, *8*(1), 19–32. Retrieved from `https://doi.org/10.1080/1364557032000119616` doi: doi:10.1080/1364557032000119616

Bade, F. M., Vollenberg, C., Koch, J., Koch, J., & Coners, A. (2022). The dark side of process mining. how identifiable are users despite technologically anonymized data? a case study from the health sector. In C. Di Ciccio, R. Dijkman, A. del Río Ortega, & S. Rinderle-Ma (Eds.), *Business process management* (pp. 219–233). Cham: Springer International Publishing.

Berti, A., Van Zelst, S. J., & Van der Aalst, W. (2019). Process mining for python (pm4py): bridging the gap between process-and data science. *arXiv preprint arXiv:1905.06169*.

Birkle, C., Pendlebury, D. A., Schnell, J., & Adams, J. (2020, 02). Web of science as a data source for research on scientific and scholarly activity. *Quantitative Science Studies*, *1*(1), 363-376. Retrieved from `https://doi.org/10.1162/qss_a_00018` doi: doi:10.1162/qss_a_00018

Butt, N. A., Mahmood, Z., Sana, M. U., Díez, I. d. l. T., Galán, J. C., Brie, S., & Ashraf, I. (2023). Behavioral and performance analysis of a real-time case study event log: A process mining approach. *Applied Sciences*, *13*(7). Retrieved from `https://www.mdpi.com/2076-3417/13/7/4145` doi: doi:10.3390/app13074145

Chiu, T., & Jans, M. (2019, 09). Process mining of event logs: A case study evaluating internal control effectiveness. *Accounting Horizons*, *33*(3), 141-156. Retrieved from `https://doi.org/`

10.2308/acch-52458 doi: doi:10.2308/acch-52458

Claus, R., Martin, N., Janssen, E. R. C., Janssenswillen, G., Boymans, T. A. E. J., & Vanwersch, R. J. B. (2024). Using process mining to explore the impact of socio-economic status on the treatment of musculoskeletal disorders – a case study. In J. De Smedt & P. Soffer (Eds.), *Process mining workshops* (pp. 211–222). Cham: Springer Nature Switzerland. doi: doi:10.1007/978-3-031-56107-8_16

Collins, G. S., Reitsma, J. B., Altman, D. G., & Moons, K. G. (2015). Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (tripod) the tripod statement. *Circulation*, *131*(2), 211–219.

Delgado, A., & Calegari, D. (2022). Discovery and analysis of e-government business processes with process mining: a case study.

Di Federico, G., Fernández-Llatas, C., Ahmadi, Z., Shirali, M., & Burattin, A. (2024). Identifying variation in personal daily routine through process mining: A case study. In J. De Smedt & P. Soffer (Eds.), *Process mining workshops* (pp. 223–234). Cham: Springer Nature Switzerland. doi: doi:10.1007/978-3-031-56107-8_17

Garcia, C. d. S., Meincheim, A., Filho, F. C. G., Santos, E. A. P., & Scalabrin, E. E. (2019). Getting insights to improve business processes with agility: A case study using process mining. In *2019 ieee international conference on systems, man and cybernetics (smc)* (p. 1336-1343). doi: doi:10.1109/SMC.2019.8914534

Hachicha, W., Ghorbel, L., Champagnat, R., Zayani, C. A., & Amous, I. (2021). Using process mining for learning resource recommendation: A moodle case study. *Procedia Computer Science*, *192*, 853-862. Retrieved from https://www.sciencedirect.com/science/article/pii/S1877050921015763 (Knowledge-Based and Intelligent Information Engineering Systems: Proceedings of the 25th International Conference KES2021) doi: doi:https://doi.org/10.1016/j.procs.2021.08.088

Hernandez-Boussard, T., Bozkurt, S., Ioannidis, J. P., & Shah, N. H. (2020). Minimar (minimum information for medical ai reporting): Developing reporting standards for artificial intelligence in health care. *Journal of the American Medical Informatics Association*, *27*(12), 2011–2015.

Hobeck, R., Klinkmüller, C., Bandara, D., Weber, I., & Aalst, W. (2021, 08). Process mining on blockchain data: A case study of augur. In (p. 306-323). doi: doi:10.1007/978-3-030-85469-0_20

Hobeck, R., Pufahl, L., & Weber, I. (2023). Process mining on curriculum-based study data: A case study at a german university. In M. Montali, A. Senderovich, & M. Weidlich (Eds.), *Process mining workshops* (pp. 577–589). Cham: Springer Nature Switzerland. doi: doi:10.1007/978-3-031-27815-0_42

Jans, M., Alles, M. G., & Vasarhelyi, M. A. (2014). A field study on the use of process mining of event logs as an analytical procedure in auditing. *The Accounting Review*, *89*(5), 1751–1773.

Jans, M., & Eulerich, M. (2022). Process mining for financial auditing. In *Process mining handbook* (pp. 445–467). Springer International Publishing Cham.

Jokonowo, B., Claes, J., Sarno, R., & Rochimah, S. (2018). Process mining in supply chains: A systematic literature review. *International Journal of Electrical and Computer Engineering (IJECE)*, *8*(6), 4626–4636.

Kitchenham, B. (2004). Procedures for performing systematic reviews. *Keele, UK, Keele University*, *33*(2004), 1–26.

Koorn, J. J., Beerepoot, I., Dani, V. S., Lu, X., Van de Weerd, I., Leopold, H., & Reijers, H. A. (2021). Bringing rigor to the qualitative evaluation of process mining findings: An analysis and a proposal. In *2021 3rd international conference on process mining (icpm)* (pp. 120–127).

Kretzschmann, D., Park, G., Berti, A., & Van der Aalst, W. M. P. (2024). Overstock problems in a purchase-to-pay process: An object-centric process mining case study. In J. P. A. Almeida, C. Di Ciccio, & C. Kalloniatis (Eds.), *Advanced information systems engineering workshops* (pp. 347–359). Cham: Springer Nature Switzerland. doi: doi:10.1007/978-3-031-61003-5_29

Kurniati, A. P., Hall, G., Hogg, D., & Johnson, O. (2021). Process mining on the extended event log to analyse the system usage during healthcare processes (case study: The gp tab usage during chemotherapy treatments). In S. Leemans & H. Leopold (Eds.), *Process mining workshops* (pp. 330–342). Cham: Springer International Publishing. doi: doi:10.1007/978-3-030-72693-5_25

Monks, T., Currie, C. S., Onggo, B. S., Robinson, S., Kunc, M., & Taylor, S. J. (2019). Strengthening the reporting of empirical simulation studies: Introducing the stress guidelines. *Journal of Simulation*, *13*(1), 55–67.

Nai, R., Sulis, E., Marengo, E., Vinai, M., & Capecchi, S. (2023). Process mining on students' web learning traces: A case study with an ethnographic analysis. In O. Viberg, I. Jivet, P. Muñoz-Merino, M. Perifanou, & T. Papathoma (Eds.), *Responsive and sustainable educational futures* (pp. 599–604). Cham: Springer Nature Switzerland. doi: doi:10.1007/978-3-031-42682-7_48

Nogueira, A. F., & Zenha-Rela, M. (2024). Process mining software engineering practices: A case study for deployment pipelines. *Information and Software Technology*, *168*, 107392. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0950584923002471` doi: doi:https://doi.org/10.1016/j.infsof.2023.107392

Olczak, J., Pavlopoulos, J., Prijs, J., Ijpma, F. F., Doornberg, J. N., Lundström, C., ... Gordon, M. (2021). Presenting artificial intelligence, deep learning, and machine learning studies to clinicians and healthcare stakeholders: an introductory reference with a guideline and a clinical ai research (cair) checklist proposal. *Acta orthopaedica*, *92*(5), 513–525.

Pegoraro, M., Narayana, M. B. S., Benevento, E., Van der Aalst, W. M. P., Martin, L., & Marx, G. (2022). Analyzing medical data with process mining: A covid-19 case study. In W. Abramowicz, S. Auer, & M. Stróżyna (Eds.), *Business information systems workshops* (pp. 39–44). Cham: Springer International Publishing. doi: doi:10.1007/978-3-031-04216-4_4

Rojas, E., Munoz-Gama, J., Sepúlveda, M., & Capurro, D. (2016). Process mining in healthcare: A literature review. *Journal of biomedical informatics*, *61*, 224–236.

Rott, J., König, F., Häfke, H., Schmidt, M., Böhm, M., Kratsch, W., & Krcmar, H. (2023). Process mining for resilient airport operations: A case study of munich airport's turnaround process. *Journal of Air Transport Management*, *112*, 102451. Retrieved from https://www.sciencedirect.com/science/article/pii/S0969699723000947 doi: doi:https://doi.org/10.1016/j.jairtraman.2023.102451

Schulz, K. F., Altman, D. G., & Moher, D. (2010). Consort 2010 statement: updated guidelines for reporting parallel group randomised trials. *Journal of Pharmacology and pharmacotherapeutics*, *1*(2), 100–107.

Son, S., Yahya, B. N., Song, M., Choi, S., Hyeon, J., Lee, B., … Sung, N. (2014). Process mining for manufacturing process analysis: a case study. In *Proceeding of 2nd asia pacific conference on business process management, brisbane, australia.*

Sulis, E. (2023). Agent-based simulations and process mining: A green bpm case study. In F. Squazzoni (Ed.), *Advances in social simulation* (pp. 337–344). Cham: Springer Nature Switzerland. doi: doi:10.1007/978-3-031-34920-1_27

Tamburis, O., & Esposito, C. (2020). Process mining as support to simulation modeling: A hospital-based case study. *Simulation Modelling Practice and Theory*, *104*, 102149. Retrieved from https://www.sciencedirect.com/science/article/pii/S1569190X20300885 doi: doi:https://doi.org/10.1016/j.simpat.2020.102149

Valero-Ramon, Z., Fernandez-Llatas, C., Collantes, G., Valdivieso, B., & Traver, V. (2024). Understanding prostate cancer care process using process mining: A case study. In J. M. Juarez et al. (Eds.), *Explainable artificial intelligence and process mining applications for healthcare* (pp. 118–130). Cham: Springer Nature Switzerland. doi: doi:10.1007/978-3-031-54303-6_12

Van der Aalst, W. (2016). *Process mining: Data science in action* (2nd ed.). Springer Publishing Company, Incorporated.

Van Der Aalst, W., Adriansyah, A., De Medeiros, A. K. A., Arcieri, F., Baier, T., Blickle, T., … others (2012). Process mining manifesto. In *Business process management workshops: Bpm 2011 international workshops, clermont-ferrand, france, august 29, 2011, revised selected papers, part i 9* (pp. 169–194).

Van der Aalst, W. M. (2022). Process mining: a 360 degree overview. In *Process mining handbook* (pp. 3–34). Springer.

Van Eck, M. L., Lu, X., Leemans, S. J., & Van Der Aalst, W. M. (2015). Pm: a process mining project methodology. In *International conference on advanced information systems engineering* (pp. 297–313).

Velasquez, N., Anani, A., Munoz-Gama, J., & Pascual, R. (2023). Towards the application of process mining in the mining industry—an lhd maintenance process optimization case study. *Sustainability*, *15*(10). Retrieved from `https://www.mdpi.com/2071-1050/15/10/7974` doi: doi:10.3390/su15107974

Zhou, J., Armas-CerVantes, A., Bozorgi, Z. D., Otte, E., & Polyvyanyy, A. (2024). Discovering changes in cell stability using process mining: A case study. In *2024 6th international conference on process mining (icpm)* (p. 65-72). doi: doi:10.1109/ICPM63005.2024.10680661