Faculty of Business Economics

Master of Management

Master's thesis

A literature review on fairness in process mining.

CHIGOZIEM BECKY OKEKE

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Business Process Management

SUPERVISOR :
Prof. dr. Koenraad VANHOOF

MENTOR :
Mevrouw Elisavet KOUTSOVITI-KOUMERI

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FROM DATA TO FAIR DECISIONS:

AN EXPLORATION OF ETHICAL AND EQUITABLE PROCESS MINING PRACTICES

By

Okeke Chigoziem Becky

A Thesis

Submitted to the Faculty of Business Economics

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PREFACE

This thesis explores the ethical dimensions of process mining, an area of increasing relevance in the intersection of data analysis and organizational decision-making. The journey of writing this thesis has been both challenging and rewarding, offering deep insights into how fairness and equity can be integrated into process mining practices.

I extend my sincere gratitude to my supervisor (Professor Vanhoof) and my mentor (Lisa), for their invaluable guidance and support throughout this study. Their constructive feedback and encouragement were vital in shaping this work.

I hope this thesis offers meaningful contributions to the field and encourages further exploration into ethical process mining.

Okeke Chigoziem Becky

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LIST OF ABBREVIATIONS

PM - Process Mining

AI - Artificial Intelligence

ML - Machine Learning

BPM - Business Process Management

BPI - Business Process Intelligence

BPA - Business Process Analysis

BAM - Business Activity Monitoring

AF - Algorithmic Fairness

TBL - Triple Bottom Line

D&I - Diversity and Inclusion

IS - Information Systems

TPR - True Positive Rate

FPR - False Positive Rate

RDS - Responsible Data Sciences

FATE - Fairness, Accountability, Transparency, and Explainability

FACT - Fairness, Accuracy, Confidentiality, and Transparency

FAIR - Findable, Accessible, Interoperable, and Reusable

PRIME - Privacy, Responsibility, Inclusivity, Monitoring, and Explainability

ProM - Process Mining Framework

XES - eXtensible Event Stream

DALG - Data Aware Event Log Generator

k-PPPM - k-anonymity-based Privacy-Preserving Process Mining

GDPR: General Data Protection Regulation

AMIA: American Medical Informatics Association

XAI: Explainable Artificial Intelligence

ABSTRACT

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Subject: Ethical and Equitable Process Mining Practices	
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This thesis explores the ethical and equitable dimensions of process mining, a field that merges data science with business process management to derive actionable insights from data. The primary focus is on ensuring that the decision-making processes facilitated by process mining are fair and unbiased.

The research investigates the current landscape of process mining, identifying key practices and methodologies that promote ethical considerations. Central to this study is the development of the PRIME framework, which encompasses Privacy, Responsibility, Inclusivity, Monitoring, and Explainability, offering a guide for organizations to adopt ethical process mining practices. Additionally, the thesis examines how organizations can design and monitor algorithms to prevent biases and ensure transparent, accountable decision-making. It also identifies key factors influencing fair process mining, such as transparency, trust, and accountability. These factors are interdependent, creating a complex ethical landscape where neglecting one element can undermine the fairness of the entire process.

Findings from this research reveal a notable rise in academic focus on ethical considerations within process mining, particularly from 2016 onwards, indicating a heightened awareness of fairness and equity in process mining practices.

The thesis concludes that to successfully implement ethical process mining, organizations must establish clear governance models, robust data management practices, and cultivate a culture of continuous improvement. The insights provided aim to help organizations achieve fair and equitable outcomes, thereby building trust and integrity in their decision-making processes.

1. INTRODUCTION

With an ever-changing field of business and technology, the most captivating area of research lies in how data influences decision-making processes. Envision a universe where digital footprints can make reports of not just how individuals, but organizations and society navigate the complexities of their numerous processes. This is the world of process mining - a data driven methodology that extracts knowledge from raw data by analyzing event logs from information systems to discover, monitor and enhance real processes. This concept drives the outcomes of businesses while influencing technological trends.

The scope, "From Data to Fair Decisions" is more than a process; it is a journey. One that marks different data points, each holding the possibility of redefining the direction of an organization. However, the scope must encompass ethical and equitable considerations such as transparency, fairness, privacy, trust, responsible, explainable, data protection, conscious or informed consent, and mitigation of bias.

Data sorting and collection are important components of process mining, encompassing tasks such as identifying applicable data sources, preprocessing, and aggregating the data. Imagine such a practice in the healthcare sector. It is evident that this delicate sector should rely on process mining to improve patient care and foster proper doctor-patient relationship. The decision makers can carry out decisions based on data-driven insights that have the potential to impact lives. In consequence, it goes beyond efficiency. It is also about ensuring that every patient receives adequate and equitable treatment. Consequently, there is a need for a thorough exploration of ethical and equitable process mining practices.

While embarking on this research, the fundamental question emerges: How can we navigate the vast terrain of process mining while ensuring that the application is both ethically sound and operationally efficient? The solution lies in this thesis, which will place emphasis on the insights and recommendations of ethical and equitable considerations in process mining practices.

A crucial aspect of this exploration involves defining and understanding bias and fairness, which are central to the ethical considerations in process mining. Bias, as outlined by various scholars, manifests in different ways, from undue prejudice and systematic errors to demographic disparities and unfair outcomes. Fairness, similarly, involves ensuring just and equitable outcomes but varies widely in definition across different contexts. This thesis makes a notable contribution by summarizing and synthesizing diverse definitions of bias and fairness from various authors. This synthesis, presented in a table, highlights common themes such as prejudice, unfairness, systematic issues, discrimination, and the role of attributes like race and gender. By organizing these definitions and keywords, the table aids in understanding how bias and fairness impact process mining practices. This contribution is essential for developing strategies that not only enhance operational efficiency but also promote fairness and equity in data-driven decision-making.

Although the ethical and equitable narrative extends beyond algorithmic bias and the societal implications of decision-making processes, it is essential to note that there remains a noticeably unaddressed aspect – the equitable/fairness and ethical constraints within process mining methodologies. Previous studies have not thoroughly examined the ethical and equitable aspects of process mining practices, making this literature review a valuable contribution to understanding the broader context of the area. While managerial considerations may be relevant and consequential in the field of organizational management, this thesis will clarify the ethical and fair dimensions of process mining. In addition, the application of process mining techniques involves more than enhancing operational efficiency. In such cases, data needs to be carefully optimized, considering not only the efficiencies realized but the impact on individuals, stakeholder equity and the overall trustworthiness of the process.

In the rest of this thesis, we will explore the literature and delve into the existing research surrounding fair and ethical process mining, delving into frameworks that highlight the complexities between data and decision from an ethical perspective, where decisions have long-term effects on different organizations.

1.1 Background and Context of Research

To fully understand the depth and significance of the research, it is essential to delve into the background of the main theme. Numerous businesses are operated by executing different business processes. Different scholars have defined business processes in various ways, emphasizing different aspects of their structure and function. Hammer and Champy (1993) describe a business process as a collection of activities that transforms inputs into valuable outputs for the customer (p. 38). This definition pinpoints the transformation of inputs into valuable outputs, focusing on the customer as the ultimate beneficiary. Similarly, Harrington (1991) characterized a business process as "a set of activities that transform an input into an output, adding value along the way for either internal or external customers." (p. 9). Although this definition shares a likeness to Hammer and Champy's, it explicitly introduces value addition, indicating that each activity within the process contributes to improving the input. Lastly, Rummler and Brache (1990) described a business process as a sequence of steps intended to create a product or service for an external customer of the organization (p. 65). This definition particularly emphasizes the step-by-step nature of processes and their goal of delivering value to the end user. These definitions differ in their emphasis on structure, measurability, and the type of outputs, but it is clear from comparing them all that they are all concerned with the transformation of inputs to outputs with value creation for the customers.

In addition to the definitions, other scholars have identified several attributes linked to business processes. (Cao et al., 2013; Shafagatova & Van Looy, 2021; Smith et al., 2002). From the extensive list of characteristics associated with business processes, three stand out as particularly relevant to the context of process mining and its application in improving operational efficiency and economic viability:

- **Customer-focused**: Business processes are designed to create value for customers by meeting their explicit and implicit needs (Cao et al., 2013). This is crucial in process mining as it aligns with the goal of enhancing customer satisfaction by streamlining operations and reducing process inefficiencies.

- **Automation-based:** Shafagatova & Van Looy stated that most business process activities are executed and controlled using various software applications (Shafagatova & Van Looy, 2021). Automation is a key aspect in process mining, which relies on data from these systems to analyze and optimize process models and company operations.

- **Dynamic**: Business processes must remain agile to adapt to changing business environments, such as new customer preferences or competitor actions (Smith et al., 2002). Process mining supports this characteristic by providing real-time insights that help businesses adapt to changes quickly.

Drawing from various scholarly perspectives, these processes are designed to organize the activities performed within an organization, serving the primary strategic goals such as providing healthcare services, customer support or manufacturing automobiles. The field dedicated to examining and optimizing these processes is known as Business Process Management (BPM) (Dumas et al. 2018). This optimization may involve reducing process duration or minimizing operational costs (Becker et al. 2007). The genesis of process mining dates to half a century ago, emerging from the advancement of fields such as Workflow Mining, Business Process Analysis (BPA), Business Process Management (BPM), Business Activity Monitoring (BAM), and Business Process Intelligence (BPI). Key contributions to this evolution have been documented by researchers including Schimm (2004), Gartner (2008), Chang (2006), van der Aalst et al. (2007), and Alves de Medeiros et al. (2004).

Process mining, according to van der Aalst (2016), aims to systematically *identify* a process model by analyzing events captured by an enterprise system, for example, by using event data to extract process-related information (Wil van der Aalst, 2016). Fundamentally, process mining is a method of discovering, monitoring, and assessing business processes. It empowers organizations to identify inefficiencies, rectify errors and identify areas ready for improvement within their operational workflow. Consequently, businesses can streamline their process which evidently leads to higher productivity, enhanced efficiency, and increased customer satisfaction. This perspective is echoed by Reinkemeyer (2020), who asserts that process mining techniques enable organizations, with a wide range of processes, to achieve greater transparency and optimization in their workflows. Similarly, Gartner (2020) emphasizes the significance of process mining in understanding operations and performance thereby supporting operational strength. Process mining involves several key techniques: data extraction, process discovery, and conformance checking. According to van der Aalst et al. (2011), the first step in data extraction is to transform raw data into an organized and analyzable format. Subsequently, the process discovery phase entails identifying, visualizing, and analyzing the process flow in real time. The last step, conformance checking involves comparing actual operational workflows against idealized models to identify deviations, errors, and inefficiencies. (van der Aalst et al. 2011). These techniques will be discussed further in **Chapter 3.2.2**. However, the widespread use of process mining has raised ethical and equitable concerns. The use of machine learning models and algorithms for data analysis has also sparked concerns over potential biases and discriminatory practices that are supported by incomplete, flawed, or biased datasets.

Organizations today increasingly depend on machine learning-driven models to generate, communicate, and provide value, while also managing customer relationships (Davenport et al., 2020). This reliance extends to marketing managers who leverage these models to enhance customer engagement and improve marketing strategies (Kumar et al., 2020; Rust, 2020; Dwivedi et al., 2021a). According to Davenport (2018), machine learning is a critical technology in the development of AI-based applications. This perspective aligns with Syam and Sharma (2018), who suggest that machine learning is the most promising method for achieving human-level AI. Similarly, Duan et al. (2019) underscores the significance of machine learning in advancing AI, emphasizing its potential to fulfill the vision of human-level AI.

Nonetheless, understanding how process mining employs machine learning is crucial. Currently, machine learning (ML) models are commonly incorporated into process mining (PM) data pipelines to perform tasks such as data manipulation, noise filtering, anomaly identification, categorization, and forecasting (van der Aalst & Damiani, 2015). Rather than using traditional methods, process mining leverages AI and ML to automatically extract, display, and interpret process information from IT systems (Lehto, 2021). Lehto further explains that process Mining utilizes machine learning algorithms to enhance traditional process mining with artificial intelligence. These capabilities encompass several key aspects. ***Descriptive Process Mining*** involves gaining a comprehensive understanding of historical events, while ***Diagnostic Process Mining*** focuses on analyzing the reasons behind these past events. On the other hand, ***Predictive Process Mining*** is used to forecast likely future occurrences, and ***Prescriptive Process Mining*** provides recommended actions to prevent potential future problems (Lehto, 2021).

As Witten and Frank (2005) explain, there are common algorithms that include decision trees for classification tasks, clustering algorithms for grouping similar event logs, and neural networks for more complex pattern recognition and predictive analytics (Sarker, 2021). These algorithms enhance the process mining framework by enabling more accurate data transformation and less bias. Furthermore, the Process and Data Science Group from RWTH Aachen explains that combining machine learning with process mining helps organizations automatically detect weaknesses in their processes, identify underlying causes, and offer prescriptive suggestions for enhancing efficiency. Additionally, they note that machine learning can fundamentally support process mining by enhancing the quality of event logs. Given that real-world data is often prone to defects, inconsistencies, and gaps in data, machine learning techniques are essential for filtering, extracting, and refining this data, thus ensuring more accurate and reliable process mining outcomes. This approach aligns with the need to address ethical and equitable concerns by ensuring data integrity and minimizing biases (Process and Data Science Group, n.d.).

The importance of balancing ethical considerations with the benefits of process mining is emphasized by Doshi-Velez and Kim (2017). They explain the significance of interpretability and transparency in algorithms, arguing that these qualities are essential for building trust among stakeholders. They also contend that transparent and explainable algorithms not only balance ethical considerations with the benefits of process mining but also foster user trust, which is paramount for ensuring the acceptance and effective implementation of algorithmic decisions.

With organizations' growing dependence on process mining for their operational strategies, it is important to address that these ethical and fair implications will ensure that the benefits of process mining are achieved without compromising fairness, trust, transparency, or overall societal well-being. This literature review highlights the varied nature of process mining and accentuates the importance of integrating ethical considerations into its practice. Through a thorough and critical overview of previously published research, this section provides a solid foundation for the subsequent analysis and discussion, paving the way for a deeper investigation of the ethical and equitable dimensions of process mining.

1.2 Research Questions

The purpose of the thesis is to *explore ethical and fair process mining practices.* Notably, the existing literature shows a significant gap: the ethical and equitable implications of process mining techniques have not been studied thoroughly.

Main Research Question:

What are the ethical and equitable implications of process mining techniques?

This central question guides the analysis of ethical and fair process mining practices. This thesis aims to develop a framework to address the ethical and equitable implications of process mining techniques, providing a structured approach for evaluating and improving fairness and ethical considerations within the field. By offering this new framework, the research contributes to the field by enhancing the understanding of and solutions for ethical practices in process mining.

To address this, three sub-questions are suggested:

1. ***What are the main factors that affect fair process mining?***

The objective of this sub-question is to ascertain and analyze the main elements impacting the ethical and equitable application of process mining techniques. Factors such as transparency, trust, accountability, privacy, data quality, inclusivity, fairness, and algorithmic bias are anticipated to play crucial roles in this exploration. By thoroughly understanding these factors, the thesis aims to provide nuanced insights to the opportunities and challenges related to achieving fairness in process mining.

a) ***What are the recurring themes in definitions of bias and fairness, and how do these variations influence the interpretation of ethical outcomes in process mining?***

This question delves into the foundational concepts of bias and fairness, examining their definitions across different contexts. Understanding these recurring themes will help clarify how they impact the ethical considerations in process mining, thereby contributing to the analysis of the factors affecting fairness.

2. ***Are there solutions or strategies to enhance fair process mining practices?***

This second sub-question explores strategies and practices that can enhance the ethical and equitable aspects of process mining. Through scrutinizing frameworks, guidelines and ethical considerations, the research aims to retrieve actionable insights and suggestions for accessing and improving fairness in process mining techniques. The analysis of various methodologies and innovative approaches will identify opportunities to enhance transparency, accountability, responsibility, trust, and privacy within process mining practices. By examining effective management techniques, valuable insights will help foster a balance between operational efficiency and ethical considerations.

To better elucidate the focus areas and methodological approaches for each research question, the table below was created. It provides a brief summary of the research questions, highlighting the primary focus areas, methodological approaches, and the anticipated research contributions.

Research Question	Focus Areas	Methodological Approach	Research Contribution
RQ1: What are the main factors that affect fair process mining?	Transparency, trust, privacy, data quality, algorithmic bias	Literature review - **Systematic** literature review	Identification of critical factors influencing ethical and equitable process mining practices
RQ1a: What are the recurring themes in definitions of bias and fairness, and how do these variations influence the interpretation of ethical outcomes in process mining?	Definitions of bias and fairness	Thematic Analysis of Literature	Clarification of foundational concepts shaping ethical considerations in process mining
RQ2: Are there strategies to enhance fair process mining practices?	Frameworks, guidelines, ethical considerations	Systematic literature review	Formulating approaches to enhance fairness in process mining

***Table 1.1**: Overview of Research Questions, Focus Areas, Methodological Approaches, and Research Contributions*

This structure guides the direction of the thesis and ensures a comprehensive exploration and systematic analysis of the factors and strategies related to ethical and equitable process mining practices.

1.3 Thesis Outline

The thesis is organized into six main chapters, each addressing different aspects of the research and its findings.

The thesis starts with an introductory chapter that outlines the research background, objectives, and structure. The second chapter details the methodology, including the selection of databases and data management. The third chapter reviews relevant literature on process mining, covering its development, applications, and key concepts related to fairness and ethics, introducing the PRIME framework.

The fourth chapter presents the research results, discussing trends, definitions of bias and fairness, and the application of the PRIME framework to address ethical issues and ensure fairness in process mining. The fifth chapter concludes by summarizing the findings, discussing the study's limitations, and offering suggestions for future research. Lastly, the sixth chapter provides a comprehensive list of references cited throughout the thesis.

2. METHODOLOGY

2.1 Research Design

This thesis uses a qualitative research design to investigate ethical and equitable process mining practices. Qualitative research enables a deep exploration and understanding of complex phenomena by offering detailed insights into the subject. (Hennink, Hutter, & Bailey, 2020). Specifically, this research employs a **systematic review of the literature** alongside a thematic review to uncover patterns and extract meaningful insights. The systematic collection, review, and analysis of existing literature ensures the identification of core concepts, challenges, and best practices in fair process mining. To provide a well-structured overview of the research methodology, Figure 2.1 outlines the research process. The flowchart illustrates the sequential steps involved in the research, from the development of research questions to the final visualization of results. This visual representation serves as a guide, summarizing the key components of the methodology discussed in this chapter.

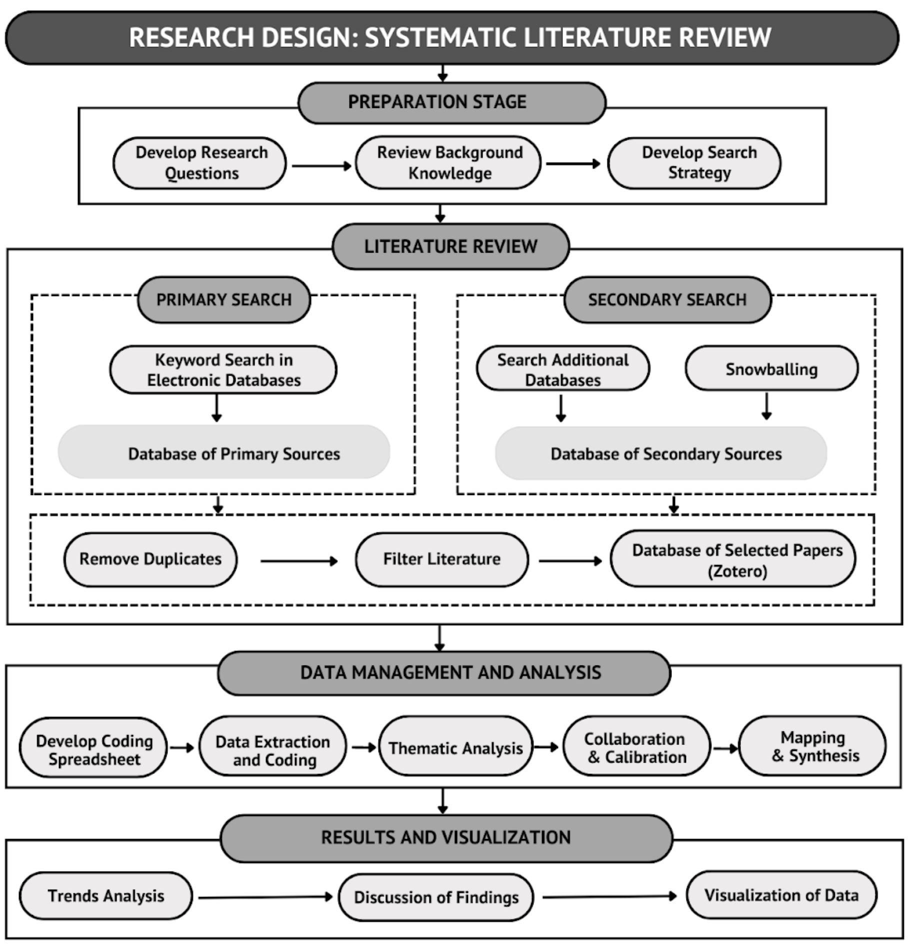

Figure 2.1: *Research Methodology Flowchart (inspired by Shams, Zowghi, and Bano, 2023)*

2.2 Review of Relevant Literature

The literature review process entailed thorough research, careful identification, selection and evaluation of relevant examination of different existing studies on process mining ethics. This process began with the development of research questions and a review of background knowledge, which were critical in defining the scope and direction of the literature review. The insights gained from this preliminary stage informed the subsequent search strategy, ensuring that it was well-targeted and comprehensive. The search strategy primarily involved the use of electronic databases of academic journals, books, and conference papers. The following databases were utilized: Google Scholar, Journal of Biomedical Informatics, SpringerLink, Science Direct, Wiley Online Library, Web of Science, and IEEE Xplore. This method ensured locating reliable sources of information on process mining while ensuring credibility and validity.

The literature search included both primary and secondary searches. Initially, a preliminary search was conducted on Google for terms related to process mining and fair process mining. This investigation helped to determine the scope of available information and adjust search parameters accordingly. Building on this foundation, optimized search terms were then used to explore additional databases, including EBSCO Host—a comprehensive database offering access to a wide array of scholarly journals, articles, and research papers (EBSCO, 2024). The searches were conducted using specific keywords to maintain relevance to the thesis, with an emphasis on narrowing down results to the most pertinent articles.

Figure 2.2 (on the right) presents a radial tree diagram that visualizes the core keywords and phrases central to this research. The diagram highlights the frequency of each keyword's mention, showcasing the terms that shaped the thesis, such as "**process mining", "bias", "privacy", "trust", "accountability", "responsible", "fair process mining", "explainable", interpretability", "data protection".** These keywords formed the foundation of the search strategy and underpin the research's thematic focus.

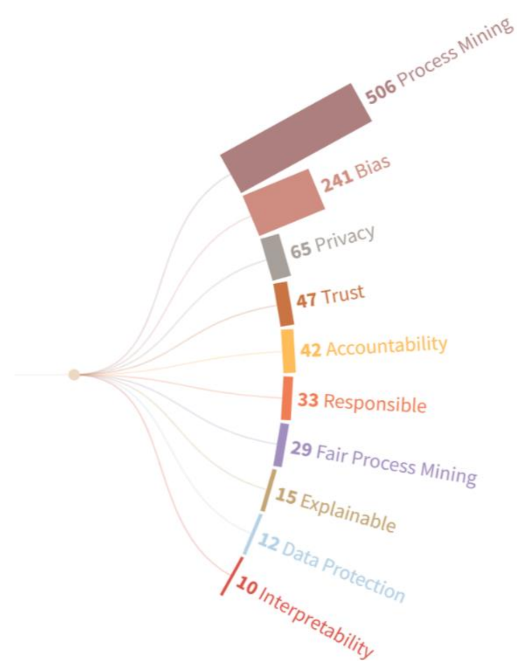

Figure 2.2: *Radial Tree Visualization of Key Concepts*

The process involved combining these search terms through logical operators, such as "AND" commands to pin-point the most narrowly defined and relevant articles. In addition, beyond the traditional database searches, this method was supplemented by snowballing techniques. These methods expanded the search scope and ensured that no potentially valuable sources were overlooked. Each source was scrutinized and carefully selected based on its alignment with the objective of the literature review.

2.3 Selection Criteria

To ensure that pertinent literature was included, the following selection criteria were applied: relevance to subject, credibility of the authors, authenticity of the information presented, diversity of perspective, date of publication, and academic thoroughness. Specifically, the criteria assessed were: a) *recency* - how up to date is the source? b) *relevance* - its alignment with the research inquiry, and c) *credibility* - the qualifications of the author(s) associated with the source. Prioritizing articles and research papers published in recent years ensured the collection of the latest insights and advancements in the process mining sector. Before filtering the literature, duplicates were removed to avoid redundancy. The remaining studies were then evaluated according to the outlined criteria and compiled into a database of selected papers.

This structured approach ensured that only the most relevant and credible sources were analyzed, facilitating a thorough review. In addition to academic databases, online platforms like Open Access and the Directory of Open Access Journals (DOAJ) were explored to identify possible sources concerning the topic. While these platforms did not present too many results related to the research, they provided broader insights into related topics and interdisciplinary perspectives.

To systematically evaluate the research landscape related to ethical and equitable process mining, the volume of publications from 2000 to 2024 was examined. This approach reveals trends and shifts in academic focus over time. The analysis indicates a significant rise in the volume of publications on the topic starting from 2016, highlighting a growing interest in ethical and equitable aspects of process mining. Prior to this period, there were relatively few sources addressing these specific concerns. These trends suggest an emerging research field with increasing scholarly attention in recent years. A detailed visualization and a deeper analysis of these trends can be found in **Chapter 4.1**, where the data overview will be discussed extensively and its implications for future research explored.

2.4 Data Management and Analysis

During the literature review process, an Excel spreadsheet was created to manage and code the sources effectively. The spreadsheet includes columns for various attributes of each source, such as the title, author(s), journal/source, summary, keywords, status, and fairness factors. A snippet of the spreadsheet is shown below:

No.	Title	Author(s)	Journal/Source	Link	Summary	Keywords	Status	Fairness Factors
1	Discrimination-Aware Process Mining: A Discussion	Timo Pohl, Mahnaz Sadat Qafari	Conference paper - 2023	Link	A method for implementing established fairness definitions in process mining	process mining, fairness, discrimination	Useful	Trust, transparency, fairness
2	Fairness, Accountability, Transparency and Explainability in Intelligent Automation	Braun et al.	ResearchGate - 2022	Link	Determine how effectively such a FATE framework fosters trust	FATE, Fairness, Accountability, Transparency, Explainability, Intelligent automation	Very Useful	Fairness, Accountability, Transparency, Explainability
3	Anonymization Techniques for Privacy Preserving Data Publishing: A Comprehensive Survey	Abdul Majeed, Sungchang Lee	Semantic Scholar (IEEE Access)	Link	Anonymization is a key technique for protecting user privacy when sharing data.	Privacy preserving data publishing, anonymization, privacy, utility	Discontinued	N/A - too technical

Table 2.1: *Overview or Snippet of Reviewed Literature on Fair Process Mining*

Each source was assessed for its relevance and usefulness, with codes indicating whether it was discontinued, useful, or very useful. This spreadsheet was used to extract and code data, with themes related to fairness in process mining being identified and recorded next to each entry, allowing for a focused analysis of the literature.

The spreadsheet provided numerous advantages to the research process. It enhanced the organization of sources, ensuring that all relevant information was systematically documented and readily accessible. This structure prevented any sources from being overlooked or misplaced, thereby maintaining a thorough database of literature. Additionally, the spreadsheet allowed for efficient data retrieval. By categorizing sources with keywords, summaries, and links, it enabled quick access to specific information, which was particularly useful when cross-referencing or revisiting studies during the writing process. Simplifying reference management was another benefit. By maintaining all reference details in one place, the spreadsheet streamlined the process of managing citations and compiling the bibliography, ensuring accurate and complete citation of all sources.

Collaboration and Calibration with the thesis supervisor were integral to the data management process. Occasional meetings helped review and validate key aspects of the research, including major findings and methodological adjustments. These discussions ensured that the coding and thematic analysis were conducted consistently and accurately. They also facilitated alignment of interpretations, refinement of the research process, and calibration of the analysis.

3. LITERATURE REVIEW

3.1 Understanding Process Mining

The historical development of process mining is closely related to the evolution of business process management (De Weerdt et al., 2013), which resulted in a convergence of ideas and technological development over several decades (van der Aalst, W., 2020). By examining important contributions that influenced the trajectory of process mining, this part of the literature review aims to offer a thorough understanding of the field's historical development. From the foundational contributions in the late 90's to its significant advancement on modern business practices, it reveals the narrative of process mining, with a focus on key developments and advancements.

3.1.1 Historical Evolution

Wil van der Aalst; a well-known Dutch professor and computer scientist, has played a significant role to the field of process mining. In fact, he is referred to as the "Godfather of process mining" being a leading figure of workflow management and process mining. Aalst recognized the limitations of traditional methods for understanding business processes in the late 1990's as traditional methods like interviews and workshops produced inconclusive and subjective process models. The term "process mining" was originally used by Aalst in a research proposal in 1998, after which formal research on the topic was initiated in 1999, marking the origin of the field of study.

Alves de Medeiros et al. (2004) introduced process mining to mine short loops in the early 2000s. By so doing, he achieved an important milestone by extending the a-algorithm which paved the way for process-related insights to be automatically extracted from event data. In that same year, Schimm focused on process mining methodologies by concentrating on mining exact models of concurrent workflows. This made it possible for businesses to understand complex interactions or relationships within their processes. This expert's contribution elevated process mining techniques to a higher layer of sophistication and opened doors to a more thorough understanding of process dynamics. Alongside these advancements, Chang (2006) investigated business process management (BPM) systems and built upon foundational concepts. He demonstrated the conceptual integration of process mining into mainstream BPM practices by emphasizing a shift from passive management to proactive engagement with processes. He analyzed the trajectory of process mining by highlighting defect prediction as a tool for software process improvement, that is, detecting defects early to proactive defect prevention. During this period, process mining was recognized as a revolutionary tool that could transform how businesses handled their processes.

In the year 2007, Wil van der Aalst pioneered the practical application of process mining in real-world industrial settings. His observations, which he shared at the 9th International Conference on Enterprise Information Systems, highlighted new developments in BPM strategies and set the stage for a business process approach that is more adaptive and dynamic. Much of his work delineates three (3) major categories or perspectives in process mining: discovery, compliance, and improvement. (IBM) *Process discovery* entails using event log data to build a process model independently, without any external influence or output. Here, the development of a new process model is not guided by any previous model. Due to its versatility and flexibility, this approach to process mining is widely used in different domains. *Compliance checking* aims to assess whether the process being observed aligns with the desired process model. This aspect involves comparing the behavior recorded in event logs to the expected behavior specified in a predefined process model. The biggest advantage is that it guarantees conformity to organizational standards and regulations by highlighting any deviations between the observed (expected) and intended procedures. *Improvement (extension organizational mining or performance mining)* is concerned with using new information to improve an existing process model. For example, insights from compliance checks can pinpoint obstacles within the process flow and ensure that managers can finetune and optimize operational workflows for improved efficacy and efficiency.

Through these forms of process mining, companies can obtain valuable understanding into their operational workflow, encouraging innovation and continuous development in their business practices. The delineation of three major categories or perspectives in process mining —discovery, compliance, and improvement- will be further elaborated upon in subsequent sections of this thesis, particularly in relation to their connection to ethical and equitable process mining.

3.1.2 Applications of Process Mining in Different Industries

Process mining, similar to a form of business intelligence system, has gained popularity in recent years or its ability to drive organizational improvements. Research by Chen et al. (2012) has highlighted its rise as a crucial tool in organizational strategy. The adoption of process mining has been linked with favorable outcomes for organizations, such as increased efficiency and operational effectiveness (Richards et al., 2019; Muller et al., 2018). These benefits are frequently attributed to the improved decision-making capabilities facilitated by actual information and data visualization (Shollo and Galliers, 2016; Olszak, 2016; Wixom and Watson, 2010).

The integration of process mining into organizational practice has unlocked new opportunities for performance improvement, which has piqued practitioners' interest (Davenport and Spanyi, 2019). Through data-driven analysis, process mining offers insights into operational processes that allows businesses to identify inefficiencies, enhance resources use and streamline workflows. This chapter highlights the applications of process mining across numerous industries, exploring its transformative impact on operational efficiency and quality improvement initiatives. Although other industries have witnessed the benefits of process mining, this subsequent section primarily examines how process mining is changing processes in healthcare, finance and human resources through several case studies and real-world examples.

3.1.2.1. Process Mining in the Healthcare Industry

In today's competitive healthcare market, hospitals are compelled to prioritize the optimization of their processes to deliver top-tier care while simultaneously managing costs (Anyanwu et al. 2003). Process mining has demonstrated significant potential in this regard. For instance, is a case study conducted in the AMC hospital in Amsterdam, focusing on the application of process mining techniques to gain insights into gynecological oncology processes, particularly the "care flows" of patients. The researchers (Ronny et al. 2015), applied a variety of process mining approaches to analyze event logs extracted from the hospital's billing system to understand patient journey, performance related data and organizational aspects.

The research findings revealed that healthcare processes, due to their dynamic characteristics and the engagement of various organizational units, provide challenges in gathering relevant data. Nevertheless, the billing system provided gynecological oncology patients with detailed information about their diagnostics and treatment procedures. The researchers pre-processed the event logs, simplified, and combined the activities, so that the data was ready for analysis (Ronny et al. 2015). From an organizational standpoint, social network mining techniques were employed to reveal collaboration patterns within hospital departments. The analysis showed strong relationships between several departments like the clinical chemistry lab which indicated major involvement in the care process. From the perspective of performance, parameters including case durations and activity patterns were visualized using dotted charts to explain overall events. These charts yielded important insights regarding patient car trajectories and use of resources (Ronny et al. 2015).

Further expanding on the AMC hospital case, Jochen De Weerdt (2012), an Associate Professor and a leading researcher in process mining, demonstrated how advanced analysis of clinical pathway data through process mining techniques can provide valuable insights into the execution of care processes. By drilling down into the clinical pathways of just over 1,000 gynecological oncology patients, De Weerdt showed that process mining could provide both high-level and detailed views of care processes, leading to enhanced efficiency and overall improvement in clinical care (De Weerdt 2012).

Another case study focused on a public hospital in Melbourne, Australia that handles more than 28,000 emergency hospital admissions annually, with a focus on patients with Acute Coronary Syndrome (ACS). The hospital faced challenges of streamlining the discharge procedure to reduce readmissions while ensuring patients' needs are met (Marcello La Rosa, 2020). To overcome this challenge, the team utilized Apromore, an open-source process mining software, to acquire insights into the discharge process. They employed a three-phase methodology to obtain thorough data to understand the patient's journey. The first step involved examining medical records and the second step involved conducting interviews with patients at different points in their hospitalization – from pre-discharge to post-discharge. This qualitative data provided significant context to enhance the medical records.

The major focus of the study involved process mining analysis using Apromore. In the third step, the team obtained a holistic view of the discharge process by retrieving and analyzing digital medical records from the hospital's patient management system. Through this method, a few critical insights were uncovered. Firstly, the analysis revealed that re-admitted patients did not undergo the same nursing assessment for discharge as non-readmitted did. This disparity demonstrated the importance of individualized nursing assessments in the discharge process and their association with lower readmission rates. Through a focus group with nursing staff, the results from the process mining analysis were evaluated. The staff verified the insights and provided additional suggestions for process improvement. This collaborative strategy ensured that the proposed modifications were informed by both front-line healthcare expertise and data-driven analysis. By finding inefficiencies in existing processes, identifying gaps in care, and providing actionable insights, process mining this hospital to improve workflow, enhance patient outcomes and reduce likelihood of readmissions (Marcello La Rosa, 2020).

Fairness in process mining is context-specific, varying by industry (Andreswari, 2024) due to different operational and ethical considerations. For instance, in healthcare, fairness might involve ensuring equitable treatment for all patient groups, while in financial services, it could focus on unbiased loan approval processes. As noted by Grenawalt (2023), transparency and accountability are essential for maintaining fairness in machine learning and process mining. These principles help prevent potential harm and ensure responsible use of data. In healthcare, the "To Err is Human" report published by the Institute of Medicine (Kohn et al., 2000) emphasized the importance of reducing medical errors, which process mining can help achieve by identifying inefficiencies and improving process transparency. Similarly, a Eurobarometer survey by the European Commission (2006) highlighted that nearly 80% of EU citizens view medical errors as a significant problem, with a notable concern among Belgian citizens. This further underscores the need for process mining tools that enhance accuracy and fairness in healthcare. Moreover, process mining in healthcare must navigate the balance between optimizing operational efficiency and maintaining patient-centered care. As noted by Jochen De Weerdt (2012), patients increasingly demand to be informed and involved in their care, highlighting the growing attention to quality and safety. This patient-centered approach aligns with the ethical imperative to ensure that process mining tools do not inadvertently prioritize efficiency over patient well-being.

In the broader context, Barocas and Selbst (2016) identify several ways AI systems can unintentionally lead to discrimination. They examine issues such as the determination of outcome variables, data labeling procedures, data collection techniques, feature selection criteria, and the use of proxy variables. These concerns are equally relevant to process mining, which, like AI, relies on data-driven insights to inform decisions (Bohanec et al., 2017). For instance, biased data or flawed analysis in process mining can result in unfair treatment of certain groups, similar to the challenges observed in AI applications. Ensuring fairness in process mining thus involves careful consideration of these factors to avoid discrimination.

The concept of "unanimous objectivity" in process mining, as described by Lars Reinkemeyer (2020), underscores the shift from subjective interpretations of process data to objective, data-driven insights. This objectivity is vital for ensuring fairness, as it reduces the potential for human bias in interpreting process flows. However, it also raises concerns about the responsible use of data and the need for robust mechanisms to ensure that process mining tools do not accidentally perpetuate or reinforce existing biases (Reinkemeyer, 2020)

These case studies illustrate how process mining may be applied in health care settings, providing insights into care flows, organizational relationships, and performance metrics. However, traditional process mining approaches encounter challenges with the intrinsically unstructured nature of healthcare processes such as complexities of hospital environments, diverse organizational units, and dynamic patient routes. (Ronny et al. 2015) Consequently, there is an urgent need for the development of innovative ways tailored to address these challenges (Pohl, 2023).

3.1.2.2. Process Mining in the Finance Industry

The ethical implications of process mining extend beyond healthcare. In various industries, ensuring fairness in process mining involves addressing potential biases in data collection, processing, and analysis. For example, in sectors like finance and human resources, process mining must account for fairness to avoid discriminatory practices that could impact individuals' financial stability or career progression.

In the financial industry, adherence to regulations is not only a legal requirement but also a critical aspect of maintaining trust and accountability. Process mining emerges as a powerful tool in this context, enabling organizations to analyze event data from their systems to create visual representations of individual cases as process flows (van der Aalst, 2017). This visualization helps to highlight deviations from standard procedures and uncover the underlying causes of non-compliance (Bots & People, 2023). A notable example of process mining's impact in the finance sector comes from a case study on Rabobank, a Dutch multinational bank. As detailed by van der Heijden (2013), Rabobank utilized process mining to enhance its procure-to-pay process, which manages over half a million invoices annually. The bank aimed to streamline its invoice processing and ensure compliance with fraud prevention regulations. By employing process mining, Rabobank gained valuable insights into its workflows, uncovering inefficiencies such as incorrect invoice entries and deliberate misuse of the "dispute" status to delay payments. These issues resulted in only 85% of invoices being paid on time, despite having a well-defined process in place.

Additionally, process mining exposed significant compliance risks, such as employees having unauthorized access to critical tasks, which heightened the risk of fraudulent activities. By tackling these problems, Rabobank improved its invoice payment rate and reinforced its compliance standards. Furthermore, the bank incorporated process mining into its daily operations, enabling ongoing monitoring and continuous improvement (van der Heijden, 2013). This case study demonstrates how process mining can profoundly enhance transparency, operational efficiency, and regulatory adherence within the financial sector.

The importance of fairness in process mining is further underscored by the Apple Card case. As reported by Vincent (2019), the Apple Card came under intense scrutiny when it was revealed that women were being assigned significantly lower credit limits than their male partners, even though both had similar financial profiles. This discrepancy was traced back to Apple’s AI-driven credit decision algorithm, which lacked sufficient fairness and transparency. The algorithm made credit limit decisions based on broad data patterns from people in the same geographic area who shopped at the same stores, rather than considering individual financial circumstances. This flawed method not only sparked widespread investigations but also dealt a severe blow to the reputations of both the Apple Card and Goldman Sachs, the financial institution behind it (Vincent, 2019).

These contrasting examples emphasize the importance of integrating fairness and transparency into process mining practices. While Rabobank's experience shows how process mining can be leveraged to enhance operational efficiency and ensure regulatory compliance, the Apple Card case serves as a caution about the dangers of neglecting these ethical considerations. Both cases highlight the role that fairness and transparency play in ensuring that technological advancements in process mining and AI benefit all stakeholders equitably, rather than perpetuating biases or unfair practices.

3.1.2.3. Process Mining in Human Resources

Building on its applications in finance, process mining also demonstrates significant potential in the field of human resources (HR). Within HR management, this technique can transform several aspects of the hiring process. For example, process mining can optimize the way applications are handled, interviews are scheduled, and onboarding processes are executed (Auxiliobits, 2023). By examining these activities, process mining not only sheds light on the efficiency of throughput times but also provides valuable insights into demographic trends, such as gender and age distributions.

This broader view stresses that while process mining brings significant advantages across various sectors, it also presents challenges related to fairness and ethical considerations. Its applications extend into industries such as production, telecommunications, sales, and services (Celonis, 2017). A review of different studies and expert opinions reveals a consensus on the need for transparency, accountability, and tailored approaches in process mining. These principles are essential to ensure that process mining tools are employed in a responsible and equitable manner, thus enhancing their value while mitigating potential ethical issues.

3.2 Tools and techniques

This subchapter explains the methods and techniques used in the field of process mining, which is essential for extracting valuable insights from event data. Most importantly, it also emphasizes the ethical dimensions of these tools, particularly their approaches to fairness and equity.

3.2.1 Common Process Mining Tools

Any tool capable of deriving process models from raw event logs, eliminating the need to for prior model creation before analysis is a process mining tool (Ailenei et al, 2012). A compilation of existing process mining software was gathered through a review of relevant literature and informal online research. Sources consulted include studies by van der Aalst et al. (2011), Tiwari, Turner, and Majeed (2008), Claes and Poels (2012a), and Ailenei (2011). The software tools, both academic and commercial are highlighted below:

Celonis: Several studies have reported that Celonis is a leading process mining platform that helps users to find and capture value quickly enough by enhancing the performance of various business processes (Ailenei 2011), (Darko et al, 2020). Founded in 2011 by three university students, Celonis has been adopted by over 500 companies globally (Celonis, 2021). It leverages advanced analytics and machine learning techniques to deliver actionable insights into organizational processes. Celonis' strengths rely on its ability to provide both on-premises and cloud-based solutions. Users may make data-driven decisions and improve overall process efficiency with the help of its AI-driven learning recommendations (Drakoulogkonas et al, 2021).

Celonis offers a comprehensive suite of services designed to enhance process transparency and efficiency. By enabling *real-time monitoring of tasks and processes*, it promptly identifies gaps and inefficiencies, ensuring organizations maintain optimal operational flow. Through its *process and task mining capabilities*, Celonis provides an in-depth view of user interactions within processes, facilitating a deeper understanding and more effective optimization (Celonis, 2021). The platform comes equipped with pre-built analyses, models, and benchmarks, making the process analysis more straightforward and accessible. In addition, Celonis supports *daily management with prioritized tasks*, actionable recommendations, and automation suggestions, ensuring managers can make informed decisions with ease. The *action flows feature* allows for seamless execution and automation of tasks across various systems, significantly boosting operational efficiency (Celonis, 2021). Moreover, Celonis offers robust *planning and simulation tools*, enabling users to design prospective processes and assess the likely effects of their decisions. By visualizing the "as-is" processes, Celonis assists companies in simplifying and streamlining their operations, thereby increasing efficiency and quality. (Celonis Labs, 2023).

More recent attention has focused on the Celonis Process Query Language (Celonis PQL). To effectively extract insights from process mining, users need to translate their process inquiries into actionable queries. In response to this, some researchers introduced Celonis PQL, a specialized language adapted to the unique data model of processes and created with business users in mind. As a fundamental component of the Celonis software platform, Celonis PQL allows any application to interact with the data model through standardized querying (Vogelgesang, 2022).

Celonis has integrated several ethical principles within its platform, emphasizing lawfulness, fairness, and transparency in data processing. For example, Celonis' core platform, the Intelligent Business Cloud (IBC), guarantees that personal data is handled in a lawful, equitable, and open or transparent manner, reinforcing accountability within its framework (Celonis Trust Center, 2023). Surpassing conventional data mining methods, AI is utilized in process mining to consistently evaluate, optimize, and monitor the analyzed processes (van der Aalst, 2012). Boucher (2020) pointed out that AI algorithms enable the platform to automatically detect patterns and provide predictive insights, which are essential for efficient process mining. Hence, while discussing Celonis, it is important to understand its commitment to ethical AI practices as these principles directly influence the dependability and fairness of the process mining outcomes.

The ethical framework of Celonis extends to its commitment to responsible AI. The platform is designed to mitigate inherent biases and discriminatory outcomes, guaranteeing that AI systems are equitable for all users and those affected by them. Transparency and explainability are prioritized, with efforts to make the functioning of AI systems clear and understandable to users, aligning with their roles and expected knowledge levels. The security and reliability of AI implementations are maintained, ensuring consistent performance across various conditions while protecting personal data in accordance with Celonis' Global Privacy Policy (Celonis Trust Center, 2023).

Governance plays a key role in Celonis' ethical AI approach, with a dedicated AI committee overseeing the responsible creation and implementation of AI technologies. This committee regularly evaluates AI initiatives, including new product features and services, ensuring they comply with internal standards and procedures. A responsible AI assessment is conducted before implementing AI initiatives, supporting compliance with Celonis' ethical principles. The platform also includes comprehensive risk management policies and procedures to assess, analyze, and manage potential risks associated with AI technologies.

Additionally, regulatory compliance is maintained through continuous monitoring of new policies and guidelines, ensuring that AI technologies are adopted and provided in accordance with legal requirements.

Aside from the IBC, The Celonis Execution Management System (EMS) exemplifies the platform's commitment to transparency and ethical process mining. According to Grimme and Hohma (2021), the Celonis' EMS autonomously detects and evaluates data patterns, providing a real-time, comprehensive view of analyzed processes. By comparing real-world processes with their digital equivalents, the EMS can detect inefficiencies and inconsistencies, providing strategic insights and revealing untapped potential to enhance operations (Rovani et al., 2015). The emphasis on transparency is a major ethical and equitable consideration in process mining, ensuring that organizations can trust the insights provided by the system.

While Celonis stands out for its integration of ethical principles in process mining, other notable tools also offer process mining functionalities and aim for transparency - some of which will be discussed in Chapter 3.4. Below are some of the other tools and their functions highlighted in the research; However, as of the latest reviews and available information, none of these tools have explicitly integrated ethical principles such as fairness and its associated factors into their platforms.

ProM: Developed at Eindhoven University of Technology in the Netherlands, Process Mining Framework (ProM) is an academic open-source framework well-known for its extensive range of plug-ins and algorithms. ProM provides a comprehensive array of tools for process discovery, conformance checking, and performance analysis, with over 500 plug-ins accessible (Ufuk and Eyüp, 2018). Being an academic platform, ProM is a leading tool in the forefront of process mining research. It offers an ideal setting for process mining scholars to study and experiment with new algorithms. Despite its strong capabilities, beginners may find it difficult to keep up with its steep learning curve. It lacks professional support and requires a certain level of expertise and experience to navigate. Therefore, professionals may view commercial process mining as a better choice to support their core activities because they are more user-friendly and practical (Ailenei 2011).

Disco: Developed by Fluxicon in the Netherlands, Disco is a commercial process mining tool that requires a customized commercial license which can be obtained through a formal request process. However, an academic license is possible for users in educational settings (Darko et al, 2020). Disco is known for its user-friendly features and easy-to-use interface. Based on the Fuzzy Miner algorithm, Disco offers integration with CSV or Excel, making it simple to import and analyze event data (Ailenei 2011). Users can easily identify bottlenecks or inefficiencies effortlessly with the help of its visualizations.

QPR ProcessAnalyzer: This flexible process mining application provides Excel plug-in options and in-browser alternatives for data analysis. A feature that stands out is its ability to directly import data from databases, facilitating the seamless integration with current IT infrastructures. QPR's MS Excel compatibility allows users to leverage well-known tools for data visualization and analysis.

Perceptive Process Mining: Developed by Perceptive Software in the United States, this process mining tool offers extensive process analysis capabilities customized to specific business requirements (Tiwari, Turner, & Majeed, 2008). As part of the Lexmark International family, perceptive process mining emphasizes usability and scalability, making it appropriate for organizations of all sizes. Its online, in-browser interface offers convenient access to process mining features from any network-based environment (Ailenei 2011).

XMAnalyzer: Developed by XMPro in the United States, offers process mining capabilities tailored to specific industrial verticals (Claes and Poels, 2012). While information about XMAnalyzer's features is scarce, its integration with XMPro's broader suite of BPM solutions suggests an emphasis on end-to-end process optimization.

InWoLvE, MinSoN, Genet/Petrify, ARIS Business Process Analysis, Signavio, Process Miner, StereoLOGIC Discovery Analyst, Rbminer/Dbminer, ExperDiTo, Fujitsu Process Analytics, and ServiceMosaic are some more process mining tools (Ailenei, 2011). While these may not be as well-known as others, they contribute to the diverse landscape of process software available. Users can easily find the tools that best fit their specific needs and preferences.

3.2.2 Analytical Techniques in Process Mining

Analytical techniques or perspectives in process mining encompasses a wide array of methods aimed at extracting valuable insights from event data. In the context of this thesis, which investigates ethical and equitable process mining practices, understanding these analytical techniques is essential for evaluating their implications on fairness, transparency, and bias mitigation.

As aforementioned, process mining techniques are crucial for understanding and enhancing corporate processes by analyzing event logs to find anomalies, bottlenecks, and inefficiencies. According to van der Aalst (2016), these techniques are broadly categorized into three groups: *process discovery, conformance checking, and process enhancement.* Each of these categories plays a vital role in understanding and optimizing business processes by analyzing event logs. However, the ethical and equitable dimension of these techniques cannot be overlooked, as biases in data collection, analysis, and interpretation can significantly impact the fairness and transparency of the insights generated (Ferrara, 2023).

Comparing various studies reveals a consensus on the necessity of ethical considerations in process mining, as several researchers have acknowledged the importance of identifying and addressing bias to create fair AI systems (Kaur, 2023; Laux, Wachter, & Mittelstadt, 2024; Strann, 2022). By integrating these perspectives, this section seeks to offer a summary of the analytical techniques in process mining, while also addressing their ethical implications.

Process Discovery as highlighted by Weerdt et al. (2012), involves extracting and visualizing process models from event logs retrospectively. The input for this type of process mining is the event log, and the expected output is a process model (van der Aalst, 2012). This perspective allows practitioners to visualize and comprehend the sequence of activities within a process. The goal is to balance complexity and precision by creating models that are both understandable and accurate. By achieving this, organizations can streamline their processes, better allocate resources, and increase overall efficiency. However, Akman and Demirörs (2009) note limitations in capturing key characteristics of process control behavior- like determining responsible roles and decision points. It is essential to recognize that the outcomes of process discovery can affect decision-making, underscoring the significance of fairness and ethical considerations in the process.

Another key technique of process mining is **Conformance checking** is a method that measures the quality of a process model and compares observed behavior against predefined process models to identify discrepancies. This technique is useful for ensuring compliance with regulations, standards, and best practices. As described by van der Aalst (2012), it evaluates the degree to which observed process behavior aligns with the expected behavior defined by a process model. Conformance checking confirms the accuracy of documented processes and identifies points of deviation for auditing and improvement purposes.

Process enhancement, as Santos Garcia et al. (2019) point out, is an addition of more information to the process models to serve as the operational support. Data is employed to fill this void, such as using in-built GPS in transport systems to precisely detect the congestion. Through enhancing process models the organizations can understand the throughput times, transition probabilities, and time- consuming transitions. (de Medeiros & van der Aalst, 2008).

Initially, efforts in the process mining domain were concentrated primarily on process discovery (van der Aalst, 2016). However, it has become increasingly evident that process discovery is merely the initial step toward process improvements. Over the past twenty years, the scope of process mining has broadened significantly. Recent progress in artificial intelligence and machine learning have extended process analysis capabilities into areas such as predictive analytics, prescriptive analytics, scenario testing, and simulation (van der Aalst, 2021; Mahsa and van de Aalst, 2021). The focus has now transitioned from retrospective analysis to prospective analysis (Reinkemeyer, 2020). As Van de Aalst (2022) notes, retrospective process mining techniques might involve diagnosing the underlying causes of inefficiencies in a production line, such as identifying why a particular issue occurs. In contrast, prospective techniques look forward, such as forecasting the remaining processing time for ongoing tasks or generating recommendations to reduce future failure rates. This shift from analyzing past data to anticipating future scenarios exemplifies the evolving capabilities within the field of process mining.

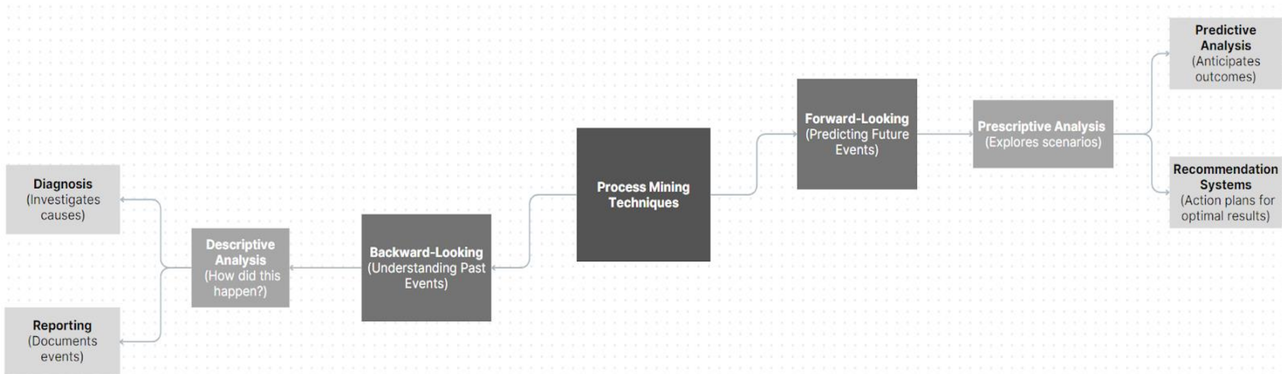

Figure 3.1: *Process Mining Techniques (Adapted from Reinkemeyer L., 2020)*

Conventional process mining techniques rely on historical data to identify issues related to compliance and conformance (van der Aalst, 2022). The Harvard Business Review (2018) emphasizes the importance of curiosity by noting how companies are interested in understanding both current events and future developments. While backward-looking process mining provides limited support for daily process management, continuous updates to event data and real-time analysis are required to enhance processes effectively. Forward-looking process mining allows for predictions regarding future events and potential deviations (van der Aalst, 2022).

3.3 Clarifying concepts: fair, ethical and equitable

To clarify the key terms used in this thesis, it is essential to delve into the foundational concepts of fairness, ethics, and equity as they relate to process mining practices. This section provides clear definitions of each concept, distinguishes between them, and highlights the importance of their significance within the context of process mining.

3.3.1 Definitions and Distinctions

Fairness: This term “fairness” denotes the characteristic of being just and unbiased. In the context of process mining, it refers to the principle that guarantees equitable treatment of all individuals or groups throughout the entire data-driven process lifecycle. This involves ensuring that no unfair bias or discrimination impacts outcomes based on attributes such as race, gender, age, or other protected characteristics. (Timo et al, 2022). Fairness entails treating all parties equally and impartially, including individuals and groups, without any bias. Fair process mining practices guarantee that data is analyzed and interpreted in a transparent, unbiased manner without any form of discrimination.

Similarly, other researchers agree that fairness in process mining underscores the need for unbiased treatment and equality. They highlight the increasing awareness that models, despite being developed with positive intentions, can still demonstrate discriminatory biases, reinforce inequities, or produce less favorable outcomes for historically marginalized groups (Barocas and Hardt 2017).

Equity: This term pertains to fairness and justice in the allocation of resources, opportunities, and results. In relation to process mining, equity ensures that all stakeholders, regardless of their backgrounds or traits, share equally in the benefits and costs of process analysis. The key terms "fairness" and "equity" are often used interchangeably, representing impartiality and just treatment. Equitable process mining practices address inequality, promote inclusivity, and uphold principles of social justice.

Ethical: This is the study of moral conduct and values that guides individuals and organizations in discerning between right and wrong behavior. Hankey and Marshall (2022) supported this meaning by stating that ethical process mining is simply "The right tool, for the right task, used in the right way". Such process mining practices adhere to moral standards such as informed consent, privacy protection, accountability, and transparency. It extends beyond technical accuracy to encompass broader societal impacts and consequences.

While fairness and equity share common principles of justice and impartiality, they function in distinct areas of process mining: Fairness and Equity essentially concerns the impartiality and objectivity of process mining practices, ensuring that data analysis is conducted without bias or discrimination. It strives to address disparities and promote equality in outcomes for all stakeholders. On the other hand, ethics guides decisions about data collection, analysis and interpretation guided by ethical principles and standards.

3.4 Ethical And Equitable Considerations in Process Mining

The development of process mining has significantly transformed how organizations use their data. According to Reinkemeyer (2022), it has allowed numerous organizations globally to gain a clearer understanding of their actual processes and to support discussions with data and facts. Reinkemeyer and Davenport (2023) further explain that while process mining initially served as a tool for addressing process performance issues on an ad hoc basis, it has gradually become a platform for continuously monitoring and improving operational efficiencies and providing strategic insights. This paradigm shift is detailed in van der Aalst's (2016) work, which describes how analyzing event logs with process mining techniques can significantly improve business processes by identifying inefficiencies. However, this advancement introduces significant ethical and equity-related considerations that require careful examination, as highlighted by numerous researchers, policymakers, and academics (Ferrara, 2023; Kleinberg et al., 2017; 2017; 2018; European Commission, 2019; Caliskan et al., Schwartz et al., 2022; Buolamwini & Gebru,). Incorporating these considerations into process mining practices is crucial to ensure that the methodology adheres to ethical standards and promotes fairness for all stakeholders.

One significant concern in process mining is privacy and data protection (Batista, Martínez-Ballesté, & Solanas, 2022). As Weippl and Schrittwieser (2024) point out, handling sensitive information requires robust mechanisms to protect individual privacy and ensure informed consent. Batista et al. (2022) emphasize that safeguarding personal data and respecting privacy are crucial for maintaining trust in process mining applications. This perspective aligns with broader literature on data ethics, which underscores the importance of protecting user information in data-driven practices (Deslée & Cloarec, 2024; Margam, 2023).

Transparency and accountability are vital elements in ethical process mining. Felzmann et al. (2019) argue that transparency regarding data sources and algorithmic processes is essential for enabling external oversight and building public trust. Their research suggests that without transparent practices, the outcomes of process mining can be misinterpreted or misused, leading to potential ethical dilemmas. Van der Aalst (2020) also stressed the importance of transparency in process mining, warning that neglecting these issues could hinder the adoption of the technology. Reinkemeyer (2020) supported this view, discussing how transparency helps organizations improve process redesign and workflow optimization, stating that clear methodologies are key to achieving sustainable and responsible results.

Bias and fairness represent another key dimension of ethical considerations in process mining. (Responsible Data Sciences [RDS], 2016). Barocas, Hardt, and Narayanan (2023), Zhang and Bareinboim (2018), and Ferrara (2023) thoroughly examine how algorithmic biases can reinforce inequalities and compromise fairness in data-driven systems and decision-making. Their research emphasizes the necessity for process mining practices to identify and reduce biases to ensure fair outcomes. Additionally, fairness and bias are critical aspects of fostering diversity, inclusivity, and equal opportunities, as they expand the understanding and application of equitable practices. This issue is particularly significant in high-impact fields like healthcare, where biases in data analysis could greatly affect patient care and results (Obermeyer et al., 2019; Bjarnadóttir & Anderson, 2020; Ahmad et al., 2020; Sripathi, 2023). An important aspect of bias and fairness in process mining is the risk of discrimination. Pohl, Qafari, and van der Aalst (2023) argue that while process mining is valuable for understanding and improving processes, it can also amplify existing biases if not carefully managed, making it essential to identify and tackle discrimination within these processes to ensure fairness.

The responsible use of process mining insights is needed for maintaining ethical and equitable standards. Mannhardt (2022) stresses that ethical decision-making requires a careful use of process mining results, prioritizing positive societal impacts over mere operational benefits. This perspective aligns with the broader discourse on the ethical use of data, which calls for balancing technological progress with its social implications (Floridi et al., 2018). Amidst the growing enthusiasm for AI, it is crucial that AI systems remain explainable to ensure ethical data usage and maintain transparency regarding their application (Reinkemeyer, 2022). Similarly, process mining must prioritize both transparency and explainability. Wil van der Aalst (2017), in his conference introduction emphasized the need for not only increased transparency but also explainability in process mining. Additionally, Marcinkevičs and Vogt (2023) underscored the importance of interpretable and explainable machine learning. This is particularly significant as machine learning (ML) and process mining (PM) often utilize similar algorithms to extract insights from data, thereby making the principles of explainability and interpretability essential for both fields (Ceravolo, Barbon Junior, Damiani, & van der Aalst, 2023).

3.4.1 Frameworks for Ethical Process Mining (The PRIME Framework)

Several existing frameworks have been developed in response to these considerations. Shin (2020) introduced the concept of FATE (Fairness, Accountability, Transparency, and Explainability), providing a foundational understanding of how these properties can guide ethical process mining practices. Similarly, Responsible Data Science (2016) proposed the FACT framework, emphasizing Fairness, Accuracy, Confidentiality, and Transparency as the four main concerns applicable to process mining. These frameworks highlight the critical elements necessary for ensuring ethical practices in data-driven methodologies. In addition, Ravi et al. (2022) created the FAIR principles, which stand for Findable, Accessible, Interoperable, and Reusable. This framework enhances the automation and reliability of AI models.

Building upon these foundational frameworks, this thesis proposes a new framework, **PRIME** (Privacy, Responsibility, Inclusivity, Monitoring, and Explainability). This acronym expands on the core elements of FATE, FACT and FAIR by incorporating additional dimensions critical to ethical process mining. The PRIME framework integrates these considerations to address a broader spectrum of ethical and equitable issues, providing an approach to evaluating and implementing process mining techniques. Each component of PRIME is designed to reinforce fairness, ensuring that process mining techniques are not only effective but also equitable. By incorporating these additional elements, PRIME seeks to enhance the balance between operational efficiency and ethical responsibility, thus advancing both organizational success and societal well-being. The following sections will explore these considerations in greater detail, addressing how each element of the PRIME framework contributes to maintaining fairness in process mining and exploring the implications for ethical practice in this field.

Figure 3.2 below illustrates the PRIME framework, highlighting principles for each component to ensure an equitable and ethical approach to process mining.

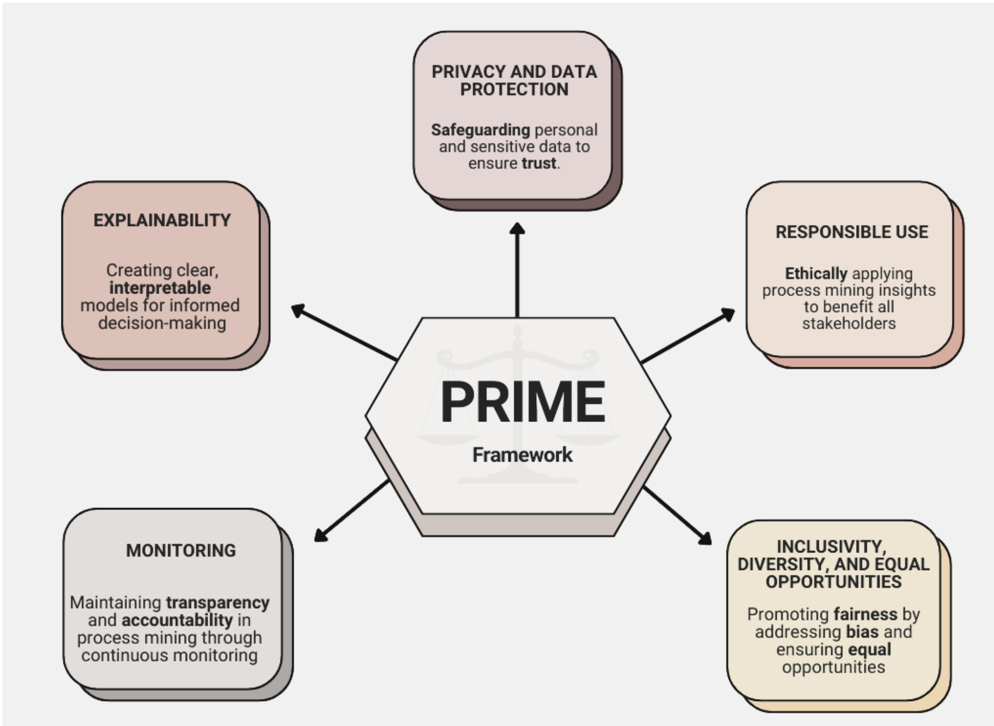

Figure 3.2: *The PRIME Framework – An Approach to Ensuring Ethical and Equitable Process Mining*

3.4.1.1. Privacy and Data Protection

Privacy and data security emerge as fundamental components in ensuring ethical and equitable application of process mining. As organizations increasingly rely on process mining to assess and optimize their business processes, they often handle vast amounts of event data that can include personal and confidential information, such as names, social security numbers, health records, socioeconomic details, and even sensitive attributes like ethnicity, sexual orientation, or religious beliefs (Batista et al., 2022). The presence of such information poses significant privacy risks, particularly in environments where process models are publicly accessible, necessitating robust privacy-preserving techniques.

In response to these challenges, researchers have proposed various solutions aimed at protecting sensitive information within event logs. For instance, Burattin et al. (2015) proposed the use of pseudonymization and encryption strategies, such as symmetric and homomorphic encryption, to safeguard confidential data during analysis. Likewise, Tillem et al. (2016) adapted the alpha algorithm—a pioneering process mining tool—to work with encrypted event logs while ensuring that privacy is maintained.

Despite these efforts, privacy and data protection in process mining remains an evolving field. Existing solutions, like pseudonymization and encryption, have been found insufficient in completely safeguarding against re-identification attacks. Rafiei et al. (2018) showed that simple encryption does not fully secure data, as encrypted information can still be susceptible to breaches. This highlights the ongoing need for more advanced privacy-preserving methods.

A promising approach is the k-PPPM (k-anonymity-based Privacy-Preserving Process Mining) method introduced by Batista et al. (2022). This technique utilizes micro aggregation to enhance privacy by preventing the re-identification of individuals, particularly in contexts vulnerable to location-based attacks. The k-PPPM method features adjustable anonymization parameters and has been tested with real-world event logs. The results demonstrated that, while process models were somewhat modified, essential relationships within the data remained intact, allowing for meaningful analysis without compromising privacy. This represents a major step forward in the field of privacy-preserving process mining (Batista et al. 2022).

However, privacy protection is not only a technical issue but also an ethical one, closely tied to the broader concept of fairness in process mining. While techniques like k-PPPM help mitigate privacy risks, they also contribute to fairness by preventing the misuse of data that could lead to biased or discriminatory outcomes. Despite the progress made with the k-PPPM method, the authors acknowledge that further improvements are needed. Striking a balance between maintaining the utility of process mining results and minimizing privacy risks remains a complex challenge (Batista et al. 2022).

3.4.1.2. Responsible Use

While safeguarding privacy and data protection is essential in ethical process mining, it is equally important to ensure that the insights derived are used responsibly. This means aligning outcomes with ethical principles such as fairness, transparency, and societal impact, thereby reinforcing trust in the methodologies used. Although research on responsible process mining is still emerging, it covers a broad range of ethical concerns, including accuracy, confidentiality, and transparency, ensuring that process mining practices are both ethical and trustworthy (Mannhardt, 2022).

Mannhardt (2022) advances the concept of responsible process mining by structuring its challenges around the FACT criteria: Fairness, Accuracy, Confidentiality, and Transparency. Drawing from van der Aalst's (2017) work, he uses a conceptual diagram to illustrate how these principles connect with responsible process mining. **Fairness**, according to Mannhardt, is crucial to avoid making unjust conclusions, even if the data appears to support them. He highlights the importance of recognizing and communicating potential biases in the data, ensuring that process mining does not inadvertently contribute to biased or discriminatory outcomes—an issue that will be examined further in later sections. **Accuracy** is another element, as outlined by van der Aalst (2017), which ensures that analysis is precise, and any potential inaccuracies are clearly communicated.ch ensures that analysis is precise, and any potential inaccuracies are clearly communicated. Mannhardt (2022) notes that while accuracy is a complex and broad topic, addressing it can be approached by focusing on two main areas: data quality and model quality, both of which are essential for preserving the accuracy of process mining results. **Confidentiality** also plays a key role, emphasizing the need to protect both sensitive and non-sensitive data within the process mining framework. Van der Aalst (2017) emphasizes that confidentiality measures should respect the privacy of all individuals involved. These measures include various techniques, such as encryption (Gentry, 2010), which is used to secure data during processing, ensuring that sensitive information is not exposed. Other strategies include group-based privacy strategies like k-anonymity, which, while effective, can be vulnerable to attacks when background knowledge is available. This risk can be mitigated through techniques like l-diversity (Machanavajjhala et al., 2007). Additionally, indistinguishability-based privacy techniques like Differential Privacy enhance protection by making individual records nearly indistinguishable from others, ensuring a higher level of data security. Finally, **Transparency** is important for conducting process mining in an open and understandable manner. This principle involves ensuring full traceability of data sources and being transparent about any issues related to data quality. By making the process mining analysis and its conclusions clear and interpretable, transparency builds stakeholder trust in the outcomes (Mannhardt, 2022). Together, these principles form a robust framework for responsible process mining, ensuring that fairness standards are consistently upheld throughout the process.

3.4.1.3. Inclusivity, Diversity and Equal Opportunities in Process Mining

Inclusivity, diversity, and equal opportunities are fundamental to ethical process mining practices. These principles are integral to ensuring that the benefits of process mining are equitably distributed and that diverse perspectives are considered in the analysis and implementation of process mining techniques. The focus on inclusivity in process mining aligns with broader societal goals of reducing discrimination and promoting fairness in data-driven decision-making processes (Dr. Varsha P . S, 2023).

Understanding the close relationship between process mining and artificial intelligence (AI) is essential. Process mining often employs AI and ML techniques to analyze and interpret complex data, and both fields face similar challenges regarding inclusivity, diversity, and ethical considerations. Integrating AI into process mining can exacerbate issues of bias and fairness if diversity and inclusion (D&I) principles are not adequately addressed. Consequently, insights from diversity and inclusion research in AI can inform and enhance process mining practices, ensuring more equitable and trustworthy outcomes (Pery et al, 2021).

The importance of inclusivity and diversity in AI is underscored by Shams, Zowghi, and Bano (2023), who argue that these principles are vital for addressing issues of trust, transparency, bias, and fairness. Considerations of diversity and inclusion are frequently neglected in the creation, development, and deployment of AI systems, which can lead to digital exclusion, discrimination, and algorithmic biases. This oversight can cause AI systems to be seen as unreliable and unjust. To tackle these issues, there

have been calls for the creation of "fairness-aware" algorithms that consider diverse populations and enhance transparency in decision-making procedures (Selbst et al., 2019).
Saheb (2023) argues that ethical considerations in AI and process mining should encompass more than just privacy and data protection, extending to diversity and inclusion as well. Zowghi and da Rimini (2023) suggest that diversity and inclusion in AI “involves integrating individuals with varied attributes and perspectives into the data, processes, systems, and governance of the AI framework”. They provide a detailed definition and guidelines for embedding principles of equity and inclusivity into AI development. Similarly, Fosch-Villaronga and Poulsen (2022) present a complementary definition of D&I in AI that considers both technical and socio-cultural dimensions. They describe inclusion “as ensuring an individual's representation within a set of instances, with better alignment between a user and relevant options signifying higher inclusion.” Diversity, in their view, pertains to the representation of individuals in relation to socio-political power disparities, such as gender and ethnic group. Adapting these definitions to process mining, diversity and inclusion can be described as integrating individuals with diverse attributes and perspectives throughout the stages of analysis, design, implementation, and governance of process mining techniques.

This integration into process mining—and other sectors—can be particularly challenging, due to limited real-world data. Techniques like the Data Aware Event Log Generator (DALG) by Jilg, Grüger, Geyer, and Bergmann (2023) and the simulation of Declare models (Di Ciccio, Bernardi, Cimitile, & Maggi, 2015) offer methods for creating synthetic event logs that adhere to fairness and ethical standards. For instance, the DALG tool provides a method for generating synthetic event logs with realistic data attributes by using semantic descriptions to ensure data relevance and quality. This approach addresses the need for high-quality data. Incorporating synthetic event log generation techniques like DALG into process mining practices can also help overcome the challenges of limited data diversity. By adhering to fairness and ethical constraints, these methods allow researchers to integrate diverse attributes effectively and ensure that the benefits of process mining are distributed more equitably.

Despite the significance of these principles, research on inclusivity, diversity, and equal opportunities in process mining remains limited. To date, no comprehensive literature review has been identified in this area. Although Shams et al. (2023) performed a systematic review on diversity and inclusion in AI, their results are not specifically relevant to process mining. This gap highlights the necessity for additional research to explore how D&I and other principles can be effectively incorporated into process mining methodologies.

Given the limited research on diversity and inclusion, it is crucial to consider related ethical dimensions that have garnered more attention, such as bias and fairness. While research on bias and fairness in process mining is still developing, it provides valuable insights that can inform broader D&I efforts. Addressing bias and ensuring fairness are fundamental to promoting ethical process mining practices, and these principles are closely aligned with the goals of inclusivity and diversity. Therefore, the following section delves into the existing research on bias and fairness, examining how these issues impact process mining and what measures can be taken to mitigate them.

3.4.1.3.1. Bias and Fairness

Bias and fairness form a crucial subset of ethical considerations in process mining. In the field of big data and ML, the notions of fairness and bias are intricately connected and bear significant implications depending on their specific use (Majumdar, 2023). For example, Osasona et al. (2024) argue that biases in AI algorithms can reinforce or worsen existing inequalities. Whether stemming from biased training data or intrinsic algorithmic biases, the consequences can be severe, and can lead to significant adverse outcomes resulting in unfair treatment or discrimination. Hence, addressing bias is critical for developing fair AI systems (Strann, 2022; Kaur, 2023; Laux, Wachter & Mittelstadt, 2024).

3.4.1.3.1.1. Definition of Bias and Fairness

However, despite the benefits of these techniques in providing operational insights into work processes across various organizations, ethical concerns such as fairness due to various biases remain a primary consideration and have been insufficiently addressed (Andreswari, 2024). To effectively address these ethical issues, it is essential to first define and understand the concept of bias.

The term "bias" has multiple, and occasionally conflicting, interpretations. According to Scatiggio (2022), by the 16th century, "bias" had come to be associated with its present-day meaning: "an undue prejudice or unfair preconceived opinion or treatment that is not based on reason or actual experience." Ferrara (2023) defines bias as consistent error in decision-making processes that produces unfair or inequitable outcomes. In contrast, Barocas et al. (2023) emphasizes "disparity," defining bias as demographic disparities in algorithmic systems that are objectionable for societal reasons.

Meanwhile, Hellström, Dignum, and Bensch (2020) define bias as outcomes influenced by prejudices rather than impartiality. In data contexts, Olteanu et al. (2019) characterize bias as the systematic distortion of data, undermining its representativeness. In the field of AI, Mitchell et al. (2021) describe bias as model outcomes that are unjust toward marginalized groups based on attributes like gender or race. Fenwick and Molnar (2022) define bias as an AI system's unfair inclination or prejudice in its judgments, either favoring or disfavoring certain individuals or groups. The Ethics of AI (2020) defines discrimination as unequal treatment of individuals based on their group membership. Zhao et al. (2018) argue that unfairness occurs when bias leads to systematic differences where none should exist. Interestingly, Ferrer et al. (2021) note that bias is not inherently negative; it can be necessary to detect distinctions between events and patterns in data.

Given the diverse definition of bias, it is essential to also address the concept of fairness, which is closely linked to bias. Simply put, fairness involves ensuring that decisions and outcomes are just and equitable, counteracting the adverse effects of bias. However, the lack of a universally accepted definition for "fairness" is the reason it has been difficult to solve this problem (Saxena, 2019). The concept's variability across different contexts and specific applications may also contribute to its diversity. Different cultures have unique views on fairness, complicating the task of establishing a single definition that is universally accepted. According to Saxena et al. (2019), fairness broadly means making decisions without discrimination or preferential treatment towards any individual or group, regardless of their inherent or acquired traits.

The keywords that recur across definitions of both bias and fairness highlight critical themes in ethical considerations within process mining. **Prejudice** and **unfairness** are central to both concepts, signifying the focus on impartial treatment and the avoidance of favoritism or discrimination. The term **systematic** underscores how bias and unfairness can be ingrained in processes and outcomes, indicating a structural issue. **Discrimination** appears as a significant concern in discussions of both bias and fairness, reinforcing the need to address inequities. The frequent mention of **individuals/groups** and **attributes** like race and gender underscores the importance of considering demographic factors when evaluating fairness and bias. However, the inclusion of "preconceived opinion" as a unique keyword for Scatiggio underscores specific aspects of bias not commonly addressed by others. Overall, these common keywords reflect a shared understanding of the impacts of bias and fairness, despite differences in specific definitions and applications.

The table below summarizes the common keywords for both bias and fairness across the various authors, with a check mark indicating their presence:

Author	Prejudice	Unfair/Unjust	Systematic	Discrimination	Individuals/groups Attributes	Preconceived opinion
Scatiggio (2022)	✓					✓
Ferrara (2023)		✓	✓			
Barocas and Hardt (2017)				✓		
Hellström et al (2020)	✓					
Olteanu et al. (2019)			✓			
Mitchell et al. (2021)		✓			✓	
Fenwick and Molnar (2022)	✓					

The Ethics of AI (2020)				✓	✓	
Zhao et al. (2018)		✓	✓			
Ferrer et al. (2021)						
Saxena et al. (2019)	✓				✓	
Timo et al. (2022)		✓		✓	✓	

Table 3.1: *Common Keywords in Definitions of Bias and Fairness*

These varying definitions highlight the complexity of addressing both bias and fairness in process mining. Addressing these challenges requires an understanding of how biases can affect outcomes and developing strategies to ensure fairness in the analysis and application of process mining results.

3.4.1.3.1.2. Classical Fairness Metrics

Andreswari (2024) stated that process mining techniques frequently involve delicate information about clients, patients, students, or residents and their results can considerably influence the livelihoods and futures of these individuals. Traditionally, process mining research has concentrated on classical fairness metrics - such as group-based fairness and individual fairness (Barocas et al., 2017). For example, one common group-based metric is **statistical or demographic parity**, which defines fairness as the probability of a particular prediction being equal across all groups. This means ensuring that all demographic groups, such as men and women, have the same likelihood of receiving a positive outcome, like job acceptance (Barocas et al., 2017). Another key metric **is equal opportunity**, which focuses on comparing true-positive rates (TPR) across different groups (Hardt et al., 2016). When evaluating fairness, the TPR indicates the proportion of positive outcomes correctly identified by a machine learning model for each group, essentially showing how well the model correctly identifies qualified individuals within each demographic.

Additionally, **equalized odds** aim to balance not only the TPR but also the false-positive rates (FPR) across groups, providing a more comprehensive approach to fairness by ensuring both types of errors are evenly distributed (Hardt et al., 2016). In simpler terms, this means that the model should not only correctly identify the qualified individuals from all groups at similar rates but also make mistakes, like falsely identifying someone as qualified, at similar rates across those groups. This approach helps to prevent the model from being biased towards any particular group, ensuring fairer and more equitable treatment for everyone. One notable example where this fairness metric is important is the COMPAS system, an algorithm criticized for disproportionately higher false-positive rates for incorrectly labeling

Black defendants as high-risk more often than White defendants. This case will be further explored in the paper, specifically in the section focused on case studies related to fairness.

In contrast, Dwork et al. (2012) emphasized the **individual fairness** metric, focusing on the fair treatment of individuals rather than groups. Their approach seeks to ensure that similar individuals receive similar outcomes, addressing unfair treatment on a more personalized level.

3.4.1.3.1.3. Case Studies Highlighting Bias and Fairness in AI

Examining real-world instances where bias and fairness issues have arisen sheds light on the practical challenges and implications of addressing these ethical concerns in AI and process mining. Ferrara (2023) highlighted occurrences of bias in AI applications across various sectors, such as healthcare and criminal justice. Andreswari (2024) and Munoz-Gama et al. (2022) further elaborated on fairness issues in areas like criminal justice, education, hiring processes, healthcare, lending, and bureaucratic procedures within process mining. Both authors agree that fairness is a crucial aspect that has been explored in machine learning research and holds significant promise for integration into process mining algorithms to promote more equitable results. The case studies underscore the importance of addressing bias and promoting fairness in these fields.

One notable instance of biased outcomes in algorithms is the COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) system, utilized in the U.S. criminal justice system to assess a defendant's risk of reoffending. Ferrara (2023) highlights research by Angwin et al. (2016), which revealed that COMPAS exhibited significant racial biases, particularly against African-American defendants. This study found that African-Americans were disproportionately classified as high-risk compared to their white counterparts, even when they had similar criminal backgrounds. Corbett-Davies et al. (2017) further expanded on these findings by demonstrating that African-American defendants were frequently assigned elevated risk scores than white defendants with equivalent chances of reoffending. This discrepancy resulted in longer detention periods before trial, underscoring the practical implications of the algorithm's bias.

Developed by Northpointe, Inc., COMPAS is designed to assist state corrections officials with decisions about offender placement, management, and treatment. The algorithm generates risk scores from a variety of data sources, including arrest histories and demographic information. However, the findings from Angwin et al. and Corbett-Davies et al. collectively reveal that despite the tool's data-driven approach, it perpetuates racial disparities, leading to longer pre-trial detentions for African-American defendants. This illustrates how algorithmic bias can translate into tangible, unfair outcomes within the legal system.

Facial recognition technology, widely used by law enforcement, is another significant example of bias in AI systems. The National Institute of Standards and Technology (NIST) conducted a study revealing that this technology exhibits notably lower accuracy for individuals with darker skin tones, resulting in a higher rate of false positives (Schwartz et al., 2022). Supporting this, Hardesty (2018) found that several commercial facial recognition systems, including those from IBM and Microsoft, showed significant failures in accurately recognizing individuals with darker skin. Hardesty's research highlights that these algorithms often struggle with identifying darker-skinned individuals, further corroborating the concerns raised by the NIST study. Both studies illustrate the tangible impact of bias in facial recognition technology, underscoring the potential for these biases to result in serious, real-world repercussions.

In the context of generative AI systems, new types of biases have emerged. These systems, designed to create content based on input prompts, are increasingly being scrutinized for their role in perpetuating gender biases (Ferrara, 2023; Ferrara, 2023b). The impact of such biases in AI systems is becoming more apparent as they are integrated into various applications, from marketing to decision-making. One prominent example of this issue was highlighted by Nicoletti and Bass (2023), who found that text-to-image models like StableDiffusion, OpenAI's DALL-E, and Midjourney exhibited significant racial and stereotypical biases. When these AI models were asked to create images of CEOs, they mainly generated pictures of men. This pattern highlights a gender bias that echoes the actual lack of women in CEO positions in the real world. Similarly, Lambrecht and Tucker (2018) demonstrated that algorithmic bias is a significant concern in machine learning applications used for decision-making and marketing. Their study revealed that Facebook's ad placement algorithm, which was intended to be gender-neutral, inadvertently showed STEM-related job ads more frequently to men than to women, highlighting an embedded bias in the system's targeting practices.

Fairness is also a critical issue in the healthcare sector concerning AL/ML. Redler (2023) highlights that implementing Fair ML practices can help reduce biases by targeting issues across data, algorithms, and the delivery of healthcare services. This approach aims to create more equitable AI systems by addressing various sources of bias. Adelman (2007) emphasizes the impact of factors like socioeconomic status, gender, and ethnicity on healthcare delivery. For example, evidence shows that healthcare providers often dismiss pain complaints from Black women, resulting in less effective treatment and worse health outcomes for them. This demonstrates how ingrained biases can affect patient care and underscores the importance of addressing these disparities.

On the other hand, Friedler, Scheidegger, and Venkatasubramanian (2016) explore the broader challenges of ensuring fairness in machine learning. They argue that while Fair ML techniques are essential, completely eliminating bias remains a significant challenge. Their insights add depth to Redler's perspective by acknowledging that even with advanced strategies, achieving perfect fairness is complex. Both Redler and Friedler et al. agree on the necessity of ongoing efforts to enhance fairness in healthcare AI systems to mitigate these disparities and ensure all patients receive equitable treatment.

Andreswari (2024) emphasizes that analyzing fairness in AI requires preserving sensitive attributes such as race, ethnicity, religion, national origin, gender identity, marital status, and age. These attributes must be considered to assess and ensure fairness. To create AI systems that are fair and equitable, it is essential to recognize and address biases based on these attributes. Ferrera (2023) underscores the importance of incorporating fairness, transparency, and accountability in the development and use of AI systems. Addressing bias in an ethically responsible manner fosters trust, promotes acceptance, and ensures compliance with regulations. This is especially important in critical fields like healthcare, where biased AI systems can result in unequal treatment access or potential harm to patients (Obermeyer et al., 2019).

Researchers have introduced a range of evaluation methods to reduce bias within systems and tools. As discussed by Redler (2023), these include fair techniques to address biases in data, algorithms, and service delivery. In his research, Mehrabi (2021) highlighted IBM's AI Fairness 360 (AIF360) toolkit, designed to transition fairness research algorithms into industrial applications and establish a standard for evaluating fairness algorithms. This toolkit also provides a collaborative platform for fairness researchers to exchange ideas (Bellamy et al., 2018). Similarly, the Aequitas project (Saleiro et al. 2018), allows users to evaluate models using multiple bias and fairness metrics for diverse population subgroups. Aequitas generates comprehensive reports that assist analysts, AI developers, and decision-makers in making informed choices to prevent harm and discrimination against specific groups. Notably, Aequitas has been applied in various case studies, including fair recruitment processes in human resources, supporting socially disadvantaged groups, and aiding the diagnosis phase in pediatric dermatology diseases within the healthcare sector.

3.4.1.3.1.4. Sources of Bias in AI

The significance of bias and fairness is acknowledged by researchers and academics alike, and their impact is profound (Caliskan et al., 2017; Kleinberg et al., 2017). In AI, bias can originate from numerous factors such as data gathering processes, algorithmic frameworks, and human judgement or interactions (Ferrara, 2023). As machine learning models, a subset of AI systems, are trained on data, they can unintentionally incorporate and "pick up" existing biases within that data, leading to outcomes that may be unfair or discriminatory.

To understand the implications of these biases more concretely, it is essential to examine their sources within AI systems. Ferrara, (2023) explains that **data collection practices** can introduce bias if the data is not representative of all relevant groups. This occurs when information used to train machine learning models is missing key pieces of information, if it contains errors or if it is biased from the onset.

Algorithmic design bias, as described by Davenport et al. (2020) and Walsh et al. (2020), arises when the AI programs themselves are biased or flawed. Even with high-quality data, if these algorithms are built on incorrect assumptions or apply unfair criteria during decision-making, it can lead to unfairness. Hence, it is important for these models to be carefully assessed to account for diverse perspectives. Shahriar et al. (2020) break down algorithmic design bias into several key subdimensions: training data bias, model bias, and method bias. **Training data bias** arises when the dataset used to train machine learning models fails to accurately represent the target population. This issue can lead to **sample selection bias** if certain groups are underrepresented or overrepresented (Cawley & Talbot, 2010). Additionally, **label bias** may occur if the data is improperly labeled or if the model fails to account for specific subgroups effectively (Paulus & Kent, 2020). In contrast, model bias emerges from the inherent limitations and assumptions within the machine learning models themselves. When models are poorly specified, they can produce unfair outcomes that do not reflect the true nature of the data (Shahriar et al., 2020). On a different front, **method bias** involves the choices and processes used throughout the AI's development. The biases here are introduced by the methodological decisions and procedural steps taken throughout the entire lifecycle of a machine learning application. This includes everything from the initial problem definition to the deployment and continuous maintenance of the system (Walsh et al., 2020). Comparing these findings, Shahriar et al. (2020) emphasize the importance of addressing biases at multiple levels, highlighting how biases can be introduced during data collection, model design, and procedural implementation. This perspective aligns with Cawley and Talbot's (2010) and Paulus and Kent's (2020) focus on training data and labeling but extends the discussion to include the procedural and design aspects outlined by Walsh et al. (2020).

Lastly, **human judgement or user bias** arises when individuals present their own biases into the process, either deliberately or unintentionally. This may happen by providing biased data or interacting with the AI in a way that reflects their own prejudices (Ferrara, 2023). The relevance of these biases to process mining becomes evident when considering how AI and machine learning techniques are integrated into process mining methodologies. As a result, biases present in AI or ML systems can directly impact the fairness and accuracy of process mining outcomes.

3.4.1.3.1.5. Bias Mitigation Strategies in AI, ML, and PM

To address these different sources of bias, several strategies have been suggested by Ferrera (2023). One approach is **dataset augmentation**, which involves enhancing the diversity of training datasets to ensure they more accurately represent the population, thereby reducing bias. This is also crucial for ensuring that event logs in process mining accurately reflect diverse processes. Another method is the development of **bias-aware algorithms**, which are specifically designed to recognize various forms of bias and mitigate their effects on the system's outcomes. Additionally, implementing **user feedback mechanisms** allows for the collection of input from users, which can be instrumental in identifying and correcting biases within the system. These combined efforts aim to create a more balanced and fair AI environment (Ferrera, 2023) and in turn enabling continuous improvement of process mining models to ensure they remain accurate and fair.

Alongside these toolkits, there are also other ranges of methods to mitigate bias in AI, ML and PM, generally categorized into four primary approaches. Within each of these main approaches, there are several specific techniques designed to address different aspects of bias and fairness.

Pre-processing techniques involve adjusting the training data to ensure it accurately reflects all segments of the population, including historically underrepresented groups (Ferrera, 2023). As outlined by d'Alessandro, O'Neil, and LaGatta (2017), pre-processing techniques aim to transform data to eliminate underlying biases. Essentially, before training a model, these methods adjust the data to remove any inherent biases or discrimination. This can include strategies like *oversampling, under sampling, or generating synthetic data* (Koh & Liang, 2017). For instance, Buolamwini and Gebru (2018) found that oversampling individuals with darker skin tones improved the performance of facial recognition systems for this group. Other pre-processing methods involve *data augmentation*, which creates synthetic data points to better represent underrepresented groups (Zhang et al., 2018).

In-Processing Techniques focus on adjusting and refining machine learning algorithms to address discrimination during the training phase of model development (d'Alessandro, O'Neil, and LaGatta, 2017). These methods involve modifying the learning algorithms themselves to ensure fairness. When permissible, in-processing techniques can be integrated into the training process by usually by introducing constraints aimed at reducing bias. For example, changes might be made to the learning algorithm to directly incorporate fairness considerations or to enforce specific fairness constraints throughout the training process (Bellamy et al., 2018; Berk et al., 2017).

Model Selection: Kamiran and Calders (2012) introduced a method for selecting models that prioritize fairness and mitigate bias. Their approach focuses on methods that emphasize fairness, including both group fairness and individual fairness (Yan, Huang, & Soleymani, 2020; Zafar, Valera, Gomez Rodriguez, & Gummadi, 2017). For instance, ensuring demographic parity involves selecting classifiers that balance positive and negative outcomes across various demographic groups. This can be achieved through techniques such as *regularization*, which imposes penalties on models for biased predictions, or through ensemble methods that integrate several models to minimize bias (Dwork et al., 2018).

Another effective approach to mitigating bias in AI involves **post-processing decisions**, which adjusts the results of AI models to enhance fairness. This method focuses on modifying the final predictions made by the model to address any disparities that may arise. For example, d'Alessandro, O'Neil, and LaGatta (2017) explored post-processing techniques that refine model outputs to ensure that metrics such as false positive and false negative rates are balanced across different demographic groups. A notable post-processing method is achieving equalized odds, which aims to equalize the rates of false positives and false negatives among various demographic groups (Hardt, Price, & Srebro, 2016).

In the context of process mining, these bias-mitigation strategies can be applied to ensure more equitable decision-making. Pre-processing methods in process mining might involve adjusting historical process data to remove or correct biases before analyzing it. In-processing techniques could include modifying the process mining algorithms to consider fairness constraints during the analysis. Post-processing methods might involve adjusting the outcomes of process mining analyses to account for discovered biases, ensuring that decisions derived from process insights are equitable. By integrating these methods, process mining can contribute to more ethical and fair decision-making practices.

3.4.1.3.1.6. Incorporating Fairness into Process Mining Practices

The intersection of AI, ML, and PM brings to light the necessity of incorporating ethical considerations to tackle bias and promote fairness. Although a universal approach to integrating diversity, inclusion, and fairness into process mining methodologies may be challenging and even damaging (Morse et al. 2022) due to the unique needs and processes of different sectors, leveraging existing frameworks can be highly beneficial. For instance, the strategies previously discussed for mitigating bias in AI and machine learning, along with frameworks designed to integrate fairness in machine learning pipelines, such as those discussed by Ravi et al. (2022), offer valuable insights that can be adapted to process mining contexts.

Ravi et al. (2022) introduced the FAIR principles - Findable, Accessible, Interoperable, and Reusable - which provide a comprehensive framework for managing scientific data and developing AI models. Adapting these principles to process mining can help ensure that the data utilized in analyses is systematically managed, reproducible, and adheres to established best practices for AI model development. By incorporating FAIR principles, process mining can improve the quality and integrity of data used, thereby supporting more accurate and equitable decision-making processes. To further ensure bias-free datasets for training process mining algorithms, it is essential to implement rigorous data pre-processing techniques that address and rectify any inherent biases.

From a technical perspective, infusing fairness into process mining is a challenging task, primarily due to the limited availability of publicly accessible event logs. Pohl et al. (2022) addressed this by generating a set of simulated event logs using CPN IDE (formerly, CPN Tools) a specialized tool for creating detailed event logs to enhance fairness in process mining. Their work introduced 12 simulated event logs spanning four critical domains—hiring, medical care, financial services, and housing—each containing key attributes like age, citizenship, German proficiency, gender, religion, and educational background. These attributes, if mishandled, can lead to discriminatory practices within each domain.

For instance, in the hiring process, sensitive or protected groups[1] such as women or older people face higher rejection rates, fewer interview opportunities, and fewer job offers than the unprotected group[2] - such as men and younger applicants (Ravi, 2022). In the healthcare sector, these protected groups often face more complicated treatment processes, fewer thorough medical examinations, and a greater likelihood of unsuccessful treatments. In the lending or loaning industry, these groups encounter more barriers, such as appointment denials and additional conditions, which contribute to a higher rate of loan rejections. Similarly, in the renting domain, protected groups are more likely to face immediate rejections, more intense screenings, and longer tenures once they secure a rental. The analysis of these logs demonstrates that even in controlled, simulated settings, significant disparities persist between protected and non-protected groups, underscoring the importance of fairness in process mining.

The study's adherence to the FAIR principles is central to its contribution. All logs conform to the eXtensible Event Stream (XES) standard format, ensuring they work seamlessly with various process mining tools and support research across different platforms. These principles also dictate how the simulated logs are managed and disseminated: they are findable via unique and persistent identifiers (like a DOI), accessible for further use and analysis, interoperable across different systems and tools, and reusable by other researchers to replicate or expand upon the findings.

Qafari & van der Aalst (2019) also incorporate FAIR principle by performing analysis using an algorithm after the events have occurred to enhance fairness in business processes. Their research focuses on making processes more equitable by identifying and eliminating biases that may result in unfair treatment of certain groups based on characteristics such as race, age, or gender. They employ data mining techniques to identify and eliminate biases, specifically by creating two decision trees within a ProM (Process Mining framework) plug-in. One decision tree represents the current decision-making process, while the other, referred to as the "fair decision tree," is specifically adjusted to reduce or eliminate unfair bias. By comparing these two trees, the plug-in can identify instances of discrimination, ensuring that decisions are based on relevant, unbiased factors (Qafari & van der Aalst, 2019). Moreover, the research suggests that by eliminating obvious biases, other less apparent issues might surface, leading to more effective improvements in business processes. This method not only demonstrates the application of fairness in process mining but also aligns with the broader objective of applying the FAIR principles to ensure transparent and equitable practices.

Another example is Andreswari (2024), whose research focuses on integrating fairness into process mining algorithms used to analyze organizational workflows. Building on design science and algorithm engineering principles, Andreswari's methodology involves identifying fairness issues in processes, such as loan applications, developing algorithms with built-in fairness principles and assessing their

[1] Ethically recognized as needing protection from discrimination or unfair treatment (Berti & Qafari, 2023).

[2] Perceived as being less vulnerable to discrimination or bias (Berti & Qafari, 2023; Ravi, 2022).

performance for effectiveness. The proposed approach combines heuristic miner algorithms with fairness measures, addressing the challenges of working with incomplete data and underscores the importance of balancing real-time fairness interventions with post-processing techniques to ensure equitable outcomes (Andreswari, 2024).

Felix Mannhardt's work on "Responsible Process Mining" also explores how to conduct process mining ethically by focusing on key aspects like fairness, accuracy, confidentiality, and transparency. Mannhardt (2022) emphasizes the importance of protecting sensitive information within event logs, such as details about an organization's operations or individuals like patients in a hospital or employees in a company. Without proper safeguards, there's a risk of privacy breaches or unauthorized surveillance. Mannhardt points out that privacy is especially difficult to protect because even anonymized data can be vulnerable to re-identification. For instance, someone with specific background knowledge—such as details about a patient—could potentially identify that person within the data, violating privacy. This risk underscores the need for advanced privacy-preserving techniques, as simple methods like pseudonymization (replacing names with codes) are often inadequate.

Most importantly, his research discusses the role of background knowledge in privacy attacks. He explains that attackers can use pre-existing information to uncover identities in anonymized data, making it easier to breach privacy. Therefore, understanding and accounting for the background knowledge that might be available to potential attackers is crucial in developing effective privacy protection strategies in process mining.

Additionally, drawing on organizational fairness literature, including studies by Dolata, Feuerriegel, and Schwabe (2021) and Morse et al. (2022), provides further guidance on embedding fairness into process mining practices. Dolata et al. (2021) argue that fairness in algorithmic systems is not merely a technical issue but a sociotechnical one. They emphasize that fairness must be considered from both social and technical perspectives, as algorithms interact with societal structures and values. Their work highlights the need for process mining to address not only technical aspects but also the social and organizational factors that influence fairness. By adopting a sociotechnical approach, process mining can better account for how social and technical components interact, which helps in creating more nuanced and effective strategies to achieve fairness. This perspective encourages integrating fairness into process mining methodologies by considering the broader impacts on human values and the ways in which social structures and technologies influence each other. Moreover, as Tarafdar et al. (2013) suggest, Information Systems (IS) should advance research into socio technical algorithmic fairness to prevent fairness issues from becoming another 'dark side' of IT. This further underscores the necessity of an approach that aligns technical solutions with societal values.

Morse et al. (2022) emphasize two primary aspects of fairness assessments: distributive fairness and procedural fairness. Their framework for understanding the connection between algorithmic criteria and key fairness aspects assists in determining the appropriateness of specific criteria. They investigate the fairness of five algorithmic criteria proposed in the technical literature using organizational justice theory as a framework. This approach highlights two key factors that influence perceptions of fairness: distributive fairness, which concerns the fairness of the outcomes, and procedural fairness, which relates to the fairness of the processes used to reach those outcomes.

Morse et al. distinguish between metrics designed to achieve parity (equal distribution of outcomes among subgroups despite differences) and those aiming for equity (equal distribution of opportunities based on the circumstances of each subgroup). For example, demographic parity and accuracy parity fall under the parity ideals, while equality of opportunity and equalized odds fall under equity ideals. Their analysis shows that fairness through unawareness, a commonly used approach where protected attributes are removed from the data, often results in lower levels of outcome fairness. Conversely, proactive methods, such as demographic parity, strive for fairer outcomes by ensuring positive outcomes are distributed equally across different categories of a protected attribute.

Figure 3.3 (see below) illustrates the framework from Morse et al. (2022), highlighting the relationship between technical effort and distributive fairness. This diagram suggests that process mining can benefit from adopting these metrics to achieve both procedural and distributive fairness. By integrating reliability, precision, ethicality, inclusiveness, bias suppression, and correctability into process mining methodologies, organizations can ensure fairer and more equitable decision-making processes. This holistic approach to fairness can significantly enhance the credibility and acceptance of process mining outcomes, fostering trust and compliance with ethical standards.

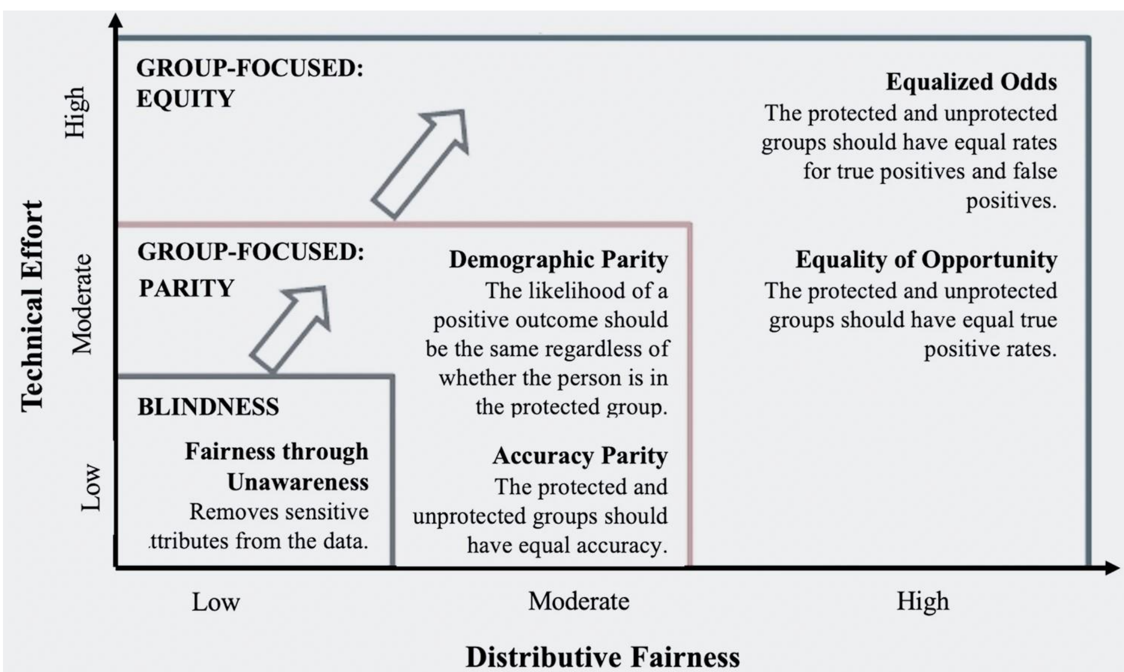

***Figure 3.3**: Framework for Distributive and Procedural Fairness in Algorithmic Systems (Source: Morse et al., 2022)*

By incorporating these established frameworks and literature, the process mining community can develop more tailored and effective strategies to address bias and promote equitable decision-making.

3.4.1.3.2. Discrimination in Process Mining

Discrimination, as an aspect of fairness, is not inherently or automatically unjust but becomes problematic when it results in harmful treatment based on group membership (Pohl, Qafari, & van der Aalst, 2023; van der Aalst, 2017). This distinction highlights that while discrimination as a concept can exist, its ethical implications are contingent upon the context and impact on individuals. The challenge of algorithmic discrimination arises when algorithms are trained on problematic data. Kim (2016) underscores that inaccuracies in training data can lead to biased outcomes, aligning with Barocas and Selbst's (2016) assertion that data reflecting pre-existing biases contributes to unfair practices. Their work together suggests a convergence on the idea that flawed data inevitably results in discriminatory outcomes. Suresh and Guttag (2019) expand this by discussing how data that fails to represent diverse groups can also result in biased decisions, adding another layer to understanding how bias manifests in algorithms. This complements the earlier points by emphasizing that even with non-biased algorithms, inadequate representation in data leads to systemic issues. Chander (2016) adds that biased data can exacerbate discriminatory practices, illustrating the cyclical nature of bias: biased data leads to biased algorithms, which then reinforce the initial biases.

To counteract these challenges, researchers have explored methods to encode fairness directly into event logs and process mining practices. One approach is presented in the work of Pohl, Qafari, and van der Aalst (2023) in their discussion on "Discrimination-Aware Process Mining." They emphasize that filtering, ranking, or decision-making steps in process mining can inadvertently cause or reinforce discrimination. The authors propose research areas such as creating evaluation criteria that consider fairness for process models and event logs and identifying and eliminating the root causes of discrimination in processes.

To further illustrate these concepts, Pohl et al. (2023) developed a detailed framework (figure 3.4) that maps the evolution of process mining techniques, and highlights stages where discrimination might occur. Building on van der Aalst's (2016) earlier work, this framework not only traces the development of process mining but also pinpoints specific stages where bias could influence outcomes. The diagram shows how real-world entities—such as individuals, business processes, and organizations— are modeled and analyzed through software systems that record interactions in event logs. These logs capture every event related to a process, including potentially discriminatory actions. Discrimination, whether intentional or unintentional, can manifest at various stages, influenced by factors like ethnicity, race, gender, disability, or sexual orientation (Pohl et al. 2023). This discrimination can stem from the process itself, its resources, or historical data. When these biased interactions are captured in event logs, they can influence the creation and refinement of process models. When process mining methods are utilized on these logs, any existing biases can be reflected or amplified, leading to unfair outcomes.

The framework particularly emphasizes how discrimination can intensify during process discovery, conformance checking, and enhancement.

The authors emphasize that ensuring fairness in process mining requires addressing potential discrimination at every stage—from data collection to the final application of the process model. This framework serves as a reminder that fairness must be an end-to-end consideration in process mining to achieve equitable outcomes.

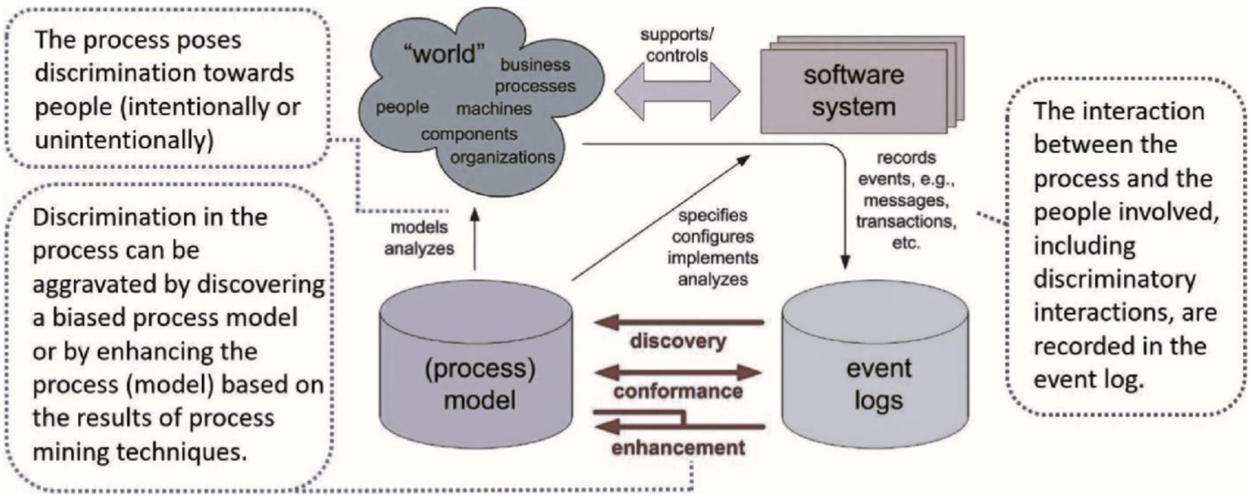

Figure 3.4: *Process Evolution Diagram Highlighting Key Process Mining Types (Source: Pohl, Qafari, and van der Aalst, 2023)*

3.4.1.4. Monitoring: Transparency and Accountability

The "Monitoring" component of the PRIME framework highlights the critical need for ongoing supervision to ensure that process mining practices maintain transparency and accountability. By establishing effective monitoring systems, organizations can continuously assess the integrity and effectiveness of their process mining activities, ensuring they adhere to ethical guidelines. This monitoring also covers various aspects such as explainability, interpretability, openness, accessibility, and visibility (Felzmann et al., 2019b). These elements reflect the broader view that transparency not only serves as a tool for resource allocation but also plays a vital role in holding those in possession of information accountable, as Forssbaeck and Oxelheim (2014) have argued.

While Felzmann et al. (2019b) emphasize the multi-faceted nature of transparency, particularly in AI contexts, Ananny and Crawford (2018) further elaborate on its role in fostering accountability. They suggest that by making systems more transparent, stakeholders can better understand the underlying logic, which in turn promotes accountability—a notion also supported by Zarsky (2013). However, as Bovens (2007) points out, transparency alone does not automatically lead to accountability. True accountability requires a deeper interaction where the responsible party not only explains their actions but also engages with those holding them to account, adding layers of complexity to the relationship between transparency and trust—a relationship that Felzmann et al. (2019a, b) is often contested in the context of AI technologies.

In process mining, both academics and practitioners recognize that increasing transparency in business processes offers substantial benefits for organizational growth. Martin et al. (2021) illustrates how transparency in process mining enables organizations to visualize actual business process flows using real-world data, thereby providing a clear and accurate representation of operations. This perspective contrasts with the challenges described by Suzor et al. (2019) in the realm of automated decision-making systems, particularly in the context of social media content moderation. Here, the lack of transparency in AI and human judgment processes often leads to confusion and dissatisfaction among users.

Regarding data transparency, Bertino et al. (2019) focus on making the processes of data collection, storage, and usage within AI systems understandable to stakeholders. Reinkemeyer (2022) supports this by emphasizing the importance of explainability in AI, which ensures that data is used ethically and transparently. This aligns with the concerns raised by Osasona (2024), who highlights the ethical challenges posed by the complexity and opacity of AI-driven decision-making processes, especially when these decisions have significant impacts on individuals or communities.

In practical applications, process mining technologies offer varying levels of transparency, as evidenced by the cases presented by different researchers. For instance, MEHRWERK GmbH's Process Mining solution, analyzed by Cotroneo et al. (2021) and Reindler (2020), was instrumental in enhancing transparency at Siemens Healthineers by standardizing workflows and addressing data inconsistencies. On the other hand, Celonis' Process Mining tool, as noted by Celonis (2017), significantly improved transparency and accountability at ABB by providing real-time insights into processes, identifying inefficiencies, and enabling benchmarking across various units. These examples show how transparency and accountability in process mining not only supports a commitment to ongoing enhancement but also highlights the different strategies and outcomes that can be achieved depending on the approach taken.

3.4.1.5. Explainable Process Mining

As processes grow more complex, especially in areas like business and healthcare, creating models that are easy to understand becomes increasingly challenging (Yeshchenko et al., 2022; Noshad, 2022). This challenge draws attention to the necessity of developing "explainable" process models that can distill complex data into forms that are easier for humans to grasp. While explainability is a concept often linked to artificial intelligence (AI)—particularly through Explainable AI (XAI), which aims to make AI's decisions and actions transparent and understandable (Bernardo, 2023)—it is equally critical in the realm of process mining (PM).

However, achieving explainability in PM presents its own set of difficulties. Hoogendoorn (2023) examined the current state of explainability in PM, seeking to inform future efforts to make these models more user-friendly and accessible. The findings, however, were inconclusive, revealing a lack of consistency in how explainability is currently addressed within PM. This inconsistency suggests that the field may not be consistently emphasizing or prioritizing explainability and interpretability across different tools, platforms, and research studies. Such a gap can undermine trust in PM results and complicate efforts to critically assess these models. Recognizing this issue, Nannini (2023) emphasizes the need to enhance the explainability of PM solutions. He proposes the development and validation of explanatory tools to address these gaps. In exploring the relationship between transparency, explainability, and interpretability, the American Medical Informatics Association (AMIA, 2022) notes that these concepts are deeply interconnected in AI contexts. Nannini's research tackles the challenge of making PM both explainable and interpretable from multiple angles. He begins by analyzing existing AI regulatory frameworks in regions like the EU, US, and UK, particularly focusing on how these regulations address XAI. This analysis aims to ensure that the development of explainable PM solutions is aligned with current regulations, making them both compliant and fair.

To complement this regulatory focus, Nannini also conducted in-depth interviews with PM practitioners to gain insights into the interpretability needs of real-world stakeholders. Drawing from these findings, he created a layered governance framework designed to help organizations systematically implement explainability and interpretability in PM. This framework guarantees that PM solutions are not only technically robust but also transparent and understandable to users. To further ensure that XAI is integrated into PM in a responsible manner, Nannini developed a proactive ethics assessment tool. This tool is designed to identify and address potential technical and socio technical risks, ensuring that the incorporation of XAI into PM is done ethically and enhances interpretability.

3.5 The Triple Bottom Line

In the early 1990’s, John Elkington (1994) presented the Triple Bottom Line (TBL) as an accounting paradigm for assessing company performance. This framework extended beyond conventional economic metrics (profit) by incorporating environmental (planet), and social dimensions (people), using specific criteria (Potts, 2004). Vanclay (2004) also supported the idea that the TBL was originally intended to ensure that business evaluations considered sustainability from an economic, environmental, and social perspective. By extending this framework to process mining, businesses can not only prioritize and integrate fairness as an essential principle but also use TBL as a powerful driver of business success.

3.5.1 People: Enhanced Equity and Stakeholder Well-being

In the context of process mining, ensuring stakeholder welfare and equity is important for creating an inclusive and ethical environment. These stakeholders include employees, suppliers, customers, and the community impacted by the company’s operations. Organizations can guarantee the safety and well-being of their employees by implementing fair process mining practices. Users can quickly respond to safety concerns, address bias, monitor employee satisfaction, deliver customer experiences, and identify potential dangers using advanced analytical techniques and inclusive data collection. This approach does not only reduce risks in an organization but promotes a supportive work environment.

3.5.2 Planet: Sustainability and Conservation

From an environmental perspective, the incorporation of fairness and ethics into process mining can support sustainability initiatives by reducing waste or eliminating unnecessary and ineffective procedures or practices. Companies can align their operations with sustainability goals by optimizing processes that will in turn minimize resources and consumption and promote fairness. However, researchers have found out that fair process mining, which has the potential to enhance sustainable business practices has been recognized by scholars and practitioners, yet it has not been thoroughly evaluated (Graves et al., 2023).

Alouidani and Elouidani (2023) explored the role of artificial intelligence (AI) in promoting sustainable decision-making and concluded that several authors highlight the significant potential of AI in this domain. For instance, Milano, O'Sullivan, and Gavanelli (2014) discuss how AI can be leveraged for policymaking to support sustainability goals. Similarly, Halsband (2022) emphasized that sustainability goes beyond just reducing ecological costs to also include considerations of intergenerational justice. Wu and Shang (2020) expand on this discussion by examining methodologies for managing uncertainty in AI-driven decision-making processes to ensure sustainable outcomes. Furthermore, Zhao and Gomez (2022) assert that AI's vast potential should undoubtedly be harnessed to advance societal well-being. They highlight that ethical considerations in AI decision-making processes can substantially contribute to environmental sustainability by ensuring transparency and reducing harmful biases. This aligns organizational operations with broader sustainability objectives. Scatiggio (2022) and Schwartz et al. (2022) note that transparency in AI -such as openly sharing data sources and the logic behind models - is essential for external review and accountability.

3.5.3 Profits: Operational Efficiency and Economic Viability

In relation to the economic aspect of the Triple Bottom Line, fairness in process mining practices can improve organizational performance and overall competitiveness. When accurate and fair process mining successfully identifies bottlenecks and inefficiencies, users can streamline these processes and maximize cost savings and improve profitability. Consequently, businesses can build trust and credibility with various stakeholders leading to long-term economic sustainability.

4. RESULTS AND DISCUSSION

This chapter presents and interprets the study's findings within the framework of ethical and equitable process mining. It begins with a detailed analysis of the data, covering trends, definitions, and relevant frameworks. The results are discussed alongside their implications, providing insights into their significance. By merging presentation and interpretation, this chapter aims to underscore the complexities of fair process mining and connect them to the broader literature and research questions addressed in this thesis.

4.1 Data Trends in Ethical and Equitable Process Mining

To achieve a complete understanding of the research landscape surrounding ethical and equitable process mining, a detailed analysis of the publication trends from 2000 to 2024 was conducted. Before delving into the analysis, it is important to note that this study is based on the publications selected and deemed useful for the development of this thesis. This subset does not represent the entirety of available literature on process mining and fair process mining. Rather, it reflects the sources that were identified as most relevant to the research questions addressed in this thesis.

The findings are visually represented in the accompanying donut chart below, illustrating the number of relevant publications per year. Each segment highlights the annual focus on this subject, offering a clear view of its evolution over time.

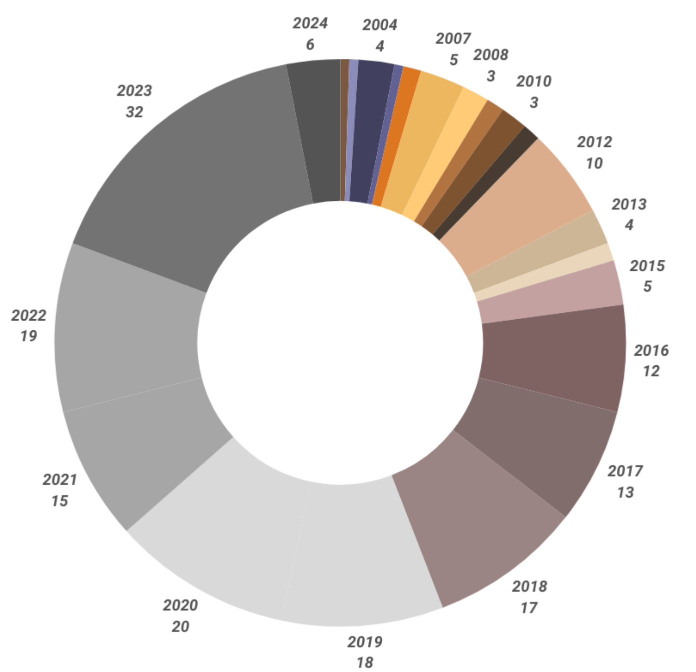

Figure 4.1: *Annual Publications on Ethical and Equitable Process Mining (2000-2024)*

The chart reveals that in the early years, from 2000 to 2015, the number of publications was relatively low, with only a few sources emerging annually. This period reflects the early development of ethical and equitable process mining, with limited academic focus. A notable shift occurred starting in 2016, marked by a significant increase in publications, culminating in a peak of 32 publications in 2023. This surge emphasizes the growing scholarly focus on ethical considerations within process mining, highlighting an increased recognition of their importance in the field.

This trend, as shown in the donut chart, indicates the emergence of ethical and equitable process mining as a significant research domain. The rising number of publications indicates increased scholarly engagement with issues related to the ethical implications and fairness of process mining practices. This shift in focus aligns with broader developments in the field, where there is a growing demand for frameworks and solutions to address these concerns.

Interestingly, these trends align with observations in related research areas. A study by Jui and Rivas (2024) also noted a similar increase in publications on fairness in machine learning and AI post-2016, mirroring the rise in process mining literature. Their findings underscore the growing academic interest in fairness-related topics within AI, which parallels the trends observed in process mining. Given the close relationship between process mining, AI, and machine learning, this correlation suggests a broader academic shift toward addressing ethical concerns across these domains.

4.2 Definitions and Implications of Bias and Fairness in Process Mining

The lack of a standardized definition of fairness underscores the complexity of addressing this issue (Saxena, 2019). Recognizing this challenge, it remains important to understand the ethical dimensions of process mining, which requires a precise definition and contextualization of key concepts like bias and fairness. This section addresses **Research Question 1a**, which explores the recurring themes in definitions of bias and fairness and how these variations influence the interpretation of ethical outcomes in process mining. By synthesizing diverse definitions from various scholars, this section provides clarity on essential themes such as prejudice, unfairness, systematic issues, discrimination, and the impact of factors such as gender, race, and age. Table 3.1, presented in **Chapter 3.4.1.3.1** illustrates these themes and serves as a tool for understanding how bias and fairness intersect with process mining practices.

The significance of this contribution lies in its ability to distill complex and varied definitions into a coherent framework. By highlighting common themes and organizing these concepts systematically, the table facilitates a clearer understanding of how bias and fairness intersect with process mining practices. For instance, the table reveals that “prejudice”, “unfair/unjust”, “individuals/groups” and "attributes**”** are the most frequently mentioned keywords across the definitions, indicating a consensus among scholars on the central role these concepts play in understanding bias. This not only clarifies the impact of these concepts on decision-making processes but also serves as an essential tool for formulating strategies that ensure both operational efficiency and equitable outcomes.

In essence, this contribution addresses a gap in the existing literature by offering a structured approach to understanding and mitigating bias and fairness in process mining. The table serves as a valuable tool for researchers and practitioners, offering a comprehensive view of how various definitions converge and diverge. This contributes to a deeper understanding of the ethical dimensions of process mining, facilitating the development of fair and unbiased data-driven decision-making processes.

4.3 Main Factors Influencing Fair Process Mining

A key insight from this research is the identification of the main factors that affect fair process mining, including transparency, trust, accountability, privacy, data quality, inclusivity, and algorithmic bias. These factors are interdependent, creating a complex ethical landscape where neglecting one element can undermine the fairness of the entire process. This section directly addresses **Research Question 1**, which seeks to determine the main factors impacting fair process mining.

For instance, insufficient transparency hampers the ability to build trust or ensure accountability, as stakeholders cannot see how decisions are made or how data is utilized, potentially leading to biases in outcomes. Similarly, without robust data quality measures, incorrect or partial data can result in flawed decision-making processes that influence fairness. This issue was exemplified in **Chapter 3.4.1.1.** Moreover, privacy concerns can complicate the collection and use of data, potentially leading to ethical dilemmas regarding consent and data protection. Privacy concerns introduce additional challenges, affecting data collection and usage. Inadequate privacy measures can result in perceived misuse of personal data, eroding trust and impacting the fairness of the process.

This interdependence suggests that any framework designed to enhance fairness in process mining must address these factors holistically. Addressing these factors collectively ensures that each element supports and enhances the others. An insightful observation from this research is that all these factors are intrinsically linked to the overarching goal of fairness in process mining. By integrating these considerations into a unified framework, it enables for a more effective and lasting approach to ensuring fairness.

4.4 The PRIME Framework in Practice: Managing Ethical Issues and Ensuring Fair Benefits in Process Mining

Scholars like Barocas and Selbst (2016) and Kim (2016) highlight the ethical dilemmas associated with algorithmic decision-making, noting that biased or incorrect data can lead to unfair and discriminatory outcomes. Turner Lee, Resnick, & Barton (2019) argue that while these biases are a significant concern, they can be mitigated through careful design and monitoring of algorithms in order to prevent any past discriminatory practices from being repeated. The significance of addressing these ethical implications cannot be overstated. This concern is echoed by Mittelstadt et al. (2016), who discuss the necessity of transparency and accountability in algorithmic processes to prevent adverse outcomes and guarantee fairness.

This section answers Research Question 2, which explores solutions or strategies to enhance fair process mining practices by discussing various ethical frameworks and mitigation strategies. To gain a clearer insight into the relationship between ethical considerations (represented by the **PRIME** framework - Privacy, Responsibility, Inclusivity, Monitoring, and Explainability), mitigation techniques, and intended outcomes in process mining, a framework was developed. This diagram below (Figure 4.2), illustrates the interactions and overlaps of these components within the framework of ethical and equitable process mining practices. Parts of the mitigation strategies within this framework were inspired by the insights provided by van der Aalst et al. (2017), the Association for Computing Machinery (2017), and Ferrara (2023).

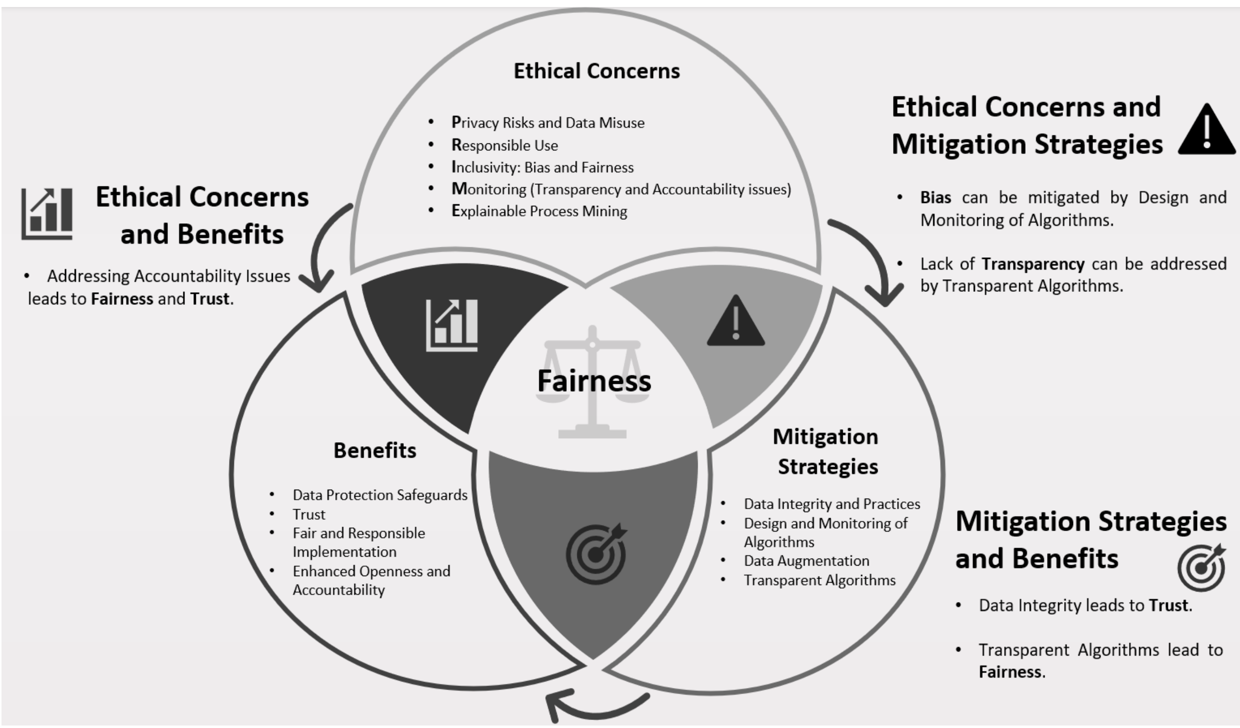

Figure 4.2: *Interconnected Framework of Ethical and Equitable Concerns in Process Mining*

The Venn diagram includes three interconnected circles: Ethical Concerns, Mitigation Strategies, and Benefits, with Fairness at the center.

Ethical concerns encompass Privacy and Data Protection, Responsible Use, Inclusivity (addressing Bias and Fairness), Monitoring (transparency and accountability issues), and Explainable Process Mining. These concerns highlight the multifaceted nature of ethics in process mining, emphasizing that addressing each area is necessary in maintaining fairness. **Mitigation strategies** include Data Integrity and Practices, Design and Monitoring of Algorithms, Data Augmentation, and Transparent Algorithms. These strategies are designed to address the ethical concerns identified, with specific measures aimed at enhancing transparency, accountability, and overall data quality. **The benefits** resulting from effective implementation of these mitigation strategies include Data Protection safeguards, Trust, Fair and Responsible Implementation, and Improved Transparency and Accountability. Each outcome is a direct response to the ethical concerns and reflects the success of the mitigation strategies in fostering fairness.

The figure illustrates that ethical concerns are interlinked with mitigation strategies and directly influence the resulting Benefits. For example, addressing accountability issues within ethical concerns directly contributes to achieving fairness and building trust. Similarly, implementing transparent algorithms enhances fairness, leading to better outcomes such as improved transparency and accountability. The central theme of the thesis - **Fairness -** integrates all these elements together, demonstrating that fairness is achieved when ethical concerns are appropriately addressed through targeted mitigation strategies, resulting in positive and responsible benefits in process mining practices.

5. CONCLUSION

5.1 Main Conclusions

This thesis has explored the ethical and equitable dimensions of process mining, aiming to bridge the gap between data-driven decision-making and ethical considerations. By investigating the complexities of bias and fairness within process mining practices, the research has provided a comprehensive synthesis of diverse definitions and identified key factors that influence fairness, including transparency, explainability, accountability, trust, and privacy. The developed framework highlights the interdependence of ethical concerns, mitigation strategies, and benefits, underscoring the necessity of a holistic approach to ensure fairness. The thesis addressed the research questions by clarifying the recurring themes in definitions of bias and fairness, evaluating the main factors affecting fair process mining, and proposing strategies to enhance ethical practices.

Organizations are encouraged to implement the proposed ethical framework and engage in continuous monitoring to maintain fairness in process mining practices. Researchers are advised to stay informed about evolving ethical standards and adapt their methodologies to incorporate new insights and best practices accordingly.

5.2 Limitations of The Research

Despite the comprehensive approach, the research faced significant limitations. Initially, the inclusion of managerial factors was anticipated, with the aim of exploring how management practices could support and influence fairness in process mining. However, the literature review revealed a notable gap in research specifically addressing the role of managerial practices in this context. This gap led to a necessary reevaluation of the thesis scope, narrowing the focus to the more established areas related to fairness.

5.2.1 Literature Gaps in Managerial Aspects

Initially, the research aimed to integrate "managerial factors" into the analysis, drawing on my background in management to explore how managerial practices and perspectives could influence fair process mining. However, a thorough search for literature specifically addressing managerial aspects in the context of process mining revealed a lack of relevant research and sources. This gap in the literature meant that integrating managerial factors into the thesis proved challenging. Hence, it resulted in time constraints as the initial scope had to be reevaluated and adjusted.

Given this limitation, the focus of the research was refined to concentrate specifically on holistic factors related to fairness in process mining. The decision to shift focus was not only guided by the available literature but also by the necessity to adapt the research timeline and ensure the thesis was grounded in established research findings. The revised focus includes trust, transparency, privacy, protection, bias, discrimination, fairness, explainability, interpretability, accountability.

By concentrating on these holistic factors, the research provides an examination of fairness in process mining, addressing key challenges and proposing solutions grounded in current literature. The thesis thus contributes to the understanding of fair process mining practices, offering valuable insights into how ethical considerations can be integrated into process mining methodologies.

5.3 Future research direction

Building on the identified literature gap, future research should explore the role of management in supporting fair process mining practices. This investigation could delve into how management practices and leadership influence the ethical dimensions of process mining and the development of frameworks that incorporate managerial perspectives. By examining the alignment between management approaches and ethical goals, researchers can gain a deeper understanding of how managerial decisions impact the fairness of process mining outcomes. This exploration could lead to the creation of guidelines that help ensure ethical practices are consistently upheld within organizations.

Additionally, future research in the field of process mining could address the need for fair process mining applications across diverse sectors. While fairness in process mining has been a prominent concern in certain industries, such as healthcare and finance, it remains underexplored in others. Comparative studies across various sectors are essential to understand how fairness considerations differ and are applied from one industry to another. Furthermore, as artificial intelligence (AI), machine learning (ML), and process mining are intricately connected, there is significant potential to further explore how principles of fairness in AI and ML can be integrated into process mining methodologies. Investigating this relationship thoroughly could offer valuable insights into how fairness can be systematically applied across these interconnected fields. Finally, conducting longitudinal studies to evaluate the long-term effects of fairness interventions and frameworks on organizational performance and stakeholder trust could provide a deeper understanding of their effectiveness over time. Addressing these areas will help fill existing literature gaps and contribute to more equitable and ethical practices in process mining.

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