Leveraging Process Mining on the Shop Floor: An Exploratory Study

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Abstract. This paper explores the potential and limitations of process mining on the shop floor in the manufacturing industry. Despite its increasing popularity, the application of process mining in manufacturing remains under-explored. Through a combination of systematic literature review and interviews with 22 industry experts, academicians, shop floor workers, and production managers, we identify key areas where process mining can be leveraged on the shop floor. Our findings can be grouped into five dimensions: organizational management & human factors, data management & quality, digitalization & technology advancements, process efficiency & optimization, and production & supply chain complexity. The findings offer a comprehensive understanding of how process mining can be leveraged to improve manufacturing processes while also addressing the organizational and technical hurdles that may impede its adoption. This study contributes to the emerging field of process science by combining findings from the literature and collecting voices on and around the shop floor. The paper closes by proposing future research and practice by incorporating organizational and human insights from the shop floor.

Keywords: Process Mining · Shop Floor · Manufacturing · Interview Study

1 Introduction

Process mining lies at the intersection of process management and data science [1] and was able to demonstrate positive effects on the increase of automation and digitalization, reduction in manual rework rate and throughput times, identification of improvement opportunities, bringing transparency and other areas in organizations of various industries including manufacturing [18]. Due to rapid

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technological advancements and globalization, the competition in the manufacturing sector is high [3]. This requires manufacturing companies to achieve optimal production efficiency and streamline processes to maintain their competitive edge [3].

To do so, manufacturing companies can use process mining to improve the organization of processes efficiently and support production planning. Specifically, an interesting area of application is on the shop floor, where the primary operational activity takes place. While some manufacturing companies have already adopted and benefited from process mining [20, 21, 7, 3], a systematic review of its application is missing [6, 4]. Still, in the last decade, the number of academic publications on the use of process mining on the shop floor has increased considerably. An examination of databases such as Scopus, EBSCO, and Web of Science reveals a marked increase in publications on this topic, with 44 new publications appearing after 2014, compared to only 4 before that year. However, compared to other industries, we see less research output for the manufacturing industry. The number of publications in the same databases for another field, like process mining in healthcare, has been over 780 in the last decade.

To better understand the current use of process mining in the manufacturing sector, this paper aims to answer the following research question: *"What opportunities does process mining bring to the operational settings on the shop floor?"*. To address the research question, we first conducted a systematic literature review, followed by qualitative research. The qualitative research was carried out through semi-structured interviews with 22 participants, who were categorized into the following personas: academicians, industry experts, shop floor workers, and production managers. The rationale for this sequence and the reasons behind our methodological choices are detailed in the methodology section. As an outcome, this paper identifies seven aggregated dimensions of process mining on the shop floor, five of which are discussed in this paper, including insights on the technologies' possibilities and limitations when applied in the industry.

The rest of the paper is structured as follows. Section 2 presents the related work. Section 3 describes and illustrates the research methodology. Section 4 presents the findings of the paper. Followed by section 5, where we discuss the findings and the limitations of our work. Finally, section 6 concludes the paper.

2 Related Work

Our research focuses on the application areas and challenges of process mining in manufacturing, particularly on the shop floor. We define the shop floor as the physical space where production activities occur, including assembly, machining, and material handling [9]. Despite the growing interest in process mining and interview studies [24], the literature specifically addressing its application on the shop floor remains notably limited. As the shop floor is part of an organization's production and supply chain, use cases and challenges have already been reported selectively in other papers.

One of the first publications looking into challenges in the production context is from Natschläger et al. [11]. The authors develop an innovative algorithm to address the complex data structures inherent in production lines, overcoming the limitations of existing algorithms. Subsequent research has explored diverse applications of process mining in manufacturing, with Netto et al. [12], Santos et al. [20], and Pourbafrani et al. [14] addressing maintenance prediction, failure diagnosis, and production performance respectively. These studies highlight process mining's potential to improve operations despite challenges like data complexity and real-time monitoring needs.

Stertz et al. [21] explore the implementation of process mining in small and medium-sized manufacturing companies. The paper emphasizes the need to address infrastructure and data collection challenges early in the implementation process. While Stertz et al. [21] touch upon the potential perception of process mining as a threat by shop floor workers, the literature examining the specific perspectives of these workers about process mining remains notably scarce.

Examining individual case studies reveals indications of challenges when implementing process mining in manufacturing, which are inherent in the characteristics of the shop floor environment, being fast-paced with a complex process structure and work steps executed by humans [9]. Concurrently, there is a notable accumulation of successful case studies that indicate a significant potential for process mining on the shop floor.

3 Research Method

Our methodology comprises a systematic literature review (see Figure 1) and semi-structured interviews. The literature review synthesized existing research with a sole focus on shop floor-related operations, as highlighted in previous studies such as Natschläger et al. [11] and Stertz et al. [21]. To fill the gap in understanding the human and operational challenges faced by workers on the shop floor, we complemented this with semi-structured interviews, capturing real-world perspectives directly from industry practitioners. Each phase is conducted with an evaluation based on predefined inclusion and exclusion criteria. Additional information on the data collection and analysis can be found in the supplementary material available on Zenodo [19].

3.1 Literature

The initial step of the literature review involved forward and backward research based on Dreher et al. [6], which conducted a systematic literature review on process mining within the full supply chain. This paper was considered a key article because it includes a broad scope that allows us to identify and focus on the specific aspects of process mining relevant to the shop floor. In the backward research step, we specifically reviewed the references cited in this article that pertained to the shop floor. This step aimed to trace the foundational studies that have significantly contributed to the understanding and application of process

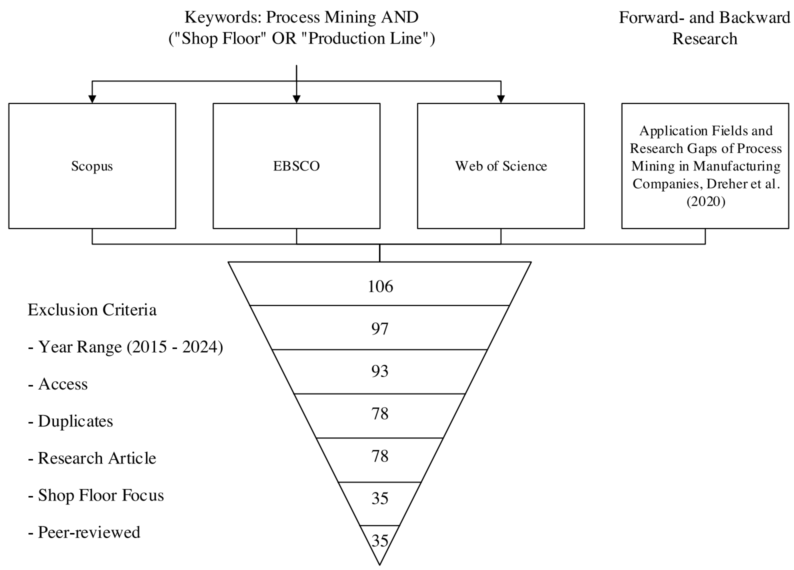

Fig. 1. Methodology for Literature Research and Interview-Based Insights

mining in the context of the shop floor. By examining these references, we identified 40 relevant articles. In the forward research step, we identified subsequent studies that have cited this key article via Google Scholar. This step focused on capturing recent developments and ongoing research trends that build upon the foundational study, resulting in an additional 21 articles. Together, this culminated in a total of 61 articles identified as relevant.

We conducted a systematic keyword-based literature review by following a scoping review. Following Paré et al. [13], we developed a review plan and research question, established a search strategy, and documented our search terms and methods. We selected the search term "process mining" AND ("shop floor" OR "production line") to reflect the most commonly used phrases for process mining in operational settings. Avoiding broader search terms such as "manufacturing" ensured that the findings remained highly relevant and specific to the shop floor activities. We excluded purchasing activities, which are part of the production process but do not directly involve shop floor operations and thus were outside this research's scope.

We searched three academic databases: EBSCO Business Source Complete, Scopus, and Web of Science. This resulted in 45 articles, increasing the total number of articles identified to 106. We filtered these articles based on exclusion and inclusion criteria. Articles published between 2015 and 2024 were included to ensure the research reflected the latest advancements in the field. Only articles accessible through institutional databases were considered, ensuring that the full text could be reviewed. Duplicate articles across different databases were identified and removed, resulting in a unique set of studies. Only peer-reviewed research articles were included to ensure the credibility of the findings. Articles specifically focusing on the shop floor within manufacturing settings were selected to maintain the research scope's relevance to the operational aspects of manufacturing. After applying these criteria, the number of articles was systematically reduced as follows: from an initial set of 106 articles, 97 articles remained after applying the year range, 93 articles after access checks, 78 articles after removing duplicates, 78 articles confirmed as research articles, and finally, 35 articles focused on the shop floor and peer-reviewed.

3.2 Interviews

We adopted a grounded theory approach to examine process mining challenges on the shop floor, using Gioia's methodology to inductively generate new insights [8]. The perception of the shop floor area was examined from multiple viewpoints during operations. These perspectives included those of academicians, industry experts, shop floor workers, and production managers, representing the four key personas in this study. We aimed to gather insights that could potentially be addressed by applying process mining techniques. For the interviews, we followed a semi-structured approach [8]. In this paper, we utilized the interviewee's work practice as a reference point to prompt participants to discuss their challenges and experiences. The semi-structured questions were divided into four sections: (i) processes and activities, (ii) challenges, (iii) strategy and communication, and (iv) goals aimed at capturing the full context of the shop floor, encompassing all its potentials and challenges.

A sampling approach was followed, with participants recruited through professional networks and via judgmental sampling [22]. We gathered data in the spring of 2024 via in-person and virtual participant interviews. Our study included interviews with two academicians, eleven industry experts, five shop floor workers, and four production managers. The interviews were transcribed using OpenAI's Whisper model [16] and manually verified against audio recordings for accuracy. On average, each interview lasted for 34 minutes.

The data analysis of the interview data consisted of two phases. First is discovery and narrowing, which includes reading the transcripts and defining a code book for tagging [15]. To facilitate the process of tagging, the tool Taguette was employed. Each interview was tagged by at least two authors, one present at the interview and one not, and all authors collectively participated in revising and refining the codes. The second phase is about enriching and validating the insights from the interviews. The applied Gioia method involves organizing qualitative data into a structured framework that begins with first-order concepts directly reflecting the interviewee's narrative [8]. Concepts are synthesized into theoretically focused second-order themes, which are then consolidated into broader, overarching aggregate dimensions. This hierarchical data structure supports theory development and captures core research findings, progressing from specific insights to more generalized theoretical constructs [8]. As a result, we obtained seven aggregated dimensions supported by 995 statements from the participants.

Table 1. Data Structure Excerpt: Concepts, Themes, and Aggregated Dimensions

1st order concepts	2nd order themes	Aggregated dimensions
Problem solving in cooperation with the team	Optimizations dependent on people	Organizational management and human factors
Different personas think about different optimizations		
New challenges require achieving goals without prior experience	Experimentation and risk-taking	
Shift to agile methods and fail-fast mindset		
Digitalization of end-to-end processes	Need for digitalization in production	Digitalization & technological advancements
Important to identify gaps in terms of digitalization of processes		
In the end only AI will help us to manage the amount of data	Future of AI	
Generative AI can simplify navigation of complex regulations		

4 Findings

The data analysis progressed from first-order concepts to second-order themes, yielding seven aggregate dimensions. Table 1 illustrates this progression for two dimensions. Although all aggregated dimensions provide valuable insights, this findings section concentrates on five aggregate dimensions, each accounting for 15 to 21 % of the total mentions. These key aggregated dimensions will be examined in greater detail in the following subsections, presented in order of declining mention percentage. Each aggregated dimension includes representative participant quotes. Participants are identified by persona (A=Academician, I=Industry expert, S=Shop Floor Worker, P=Production manager) followed by a unique number.

4.1 Organizational management & human factors

The main themes included in this aggregate dimension 'organizational management & human factors' are the importance of inter-departmental and inter-company communication, employee enablement for process mining, addressing fears of redundancy, and fostering user engagement.

One reoccurring 2nd order theme was 'Importance of Communication between departments', highlighting the need for precise, timely, and relevant information exchange, including the right information for the current situation. Starting with inter-company communication, this also extends to relationships between companies (e.g., supplier relationships) to better navigate discrepancies within the processes. Participants in our study emphasized that *"cross-functional communication is key between different departments"* (I1) and *"the supply chain needs to communicate any problems to the production so it can be adjusted in time"* (P1).

A further area of 2nd order themes within the 'organizational management & human factors' dimension reveals challenges in employee enablement for process mining, addressing redundancy fears, and fostering user engagement. The study highlights the challenge of developing effective training programs that empower employees while mitigating job security concerns. Balancing formal education with ongoing learning presents another challenge in keeping pace with industry advancements. As one interviewee noted, *"the first solution that gets implemented to the shop floor is a supporting solution"* (I2), suggesting a challenge in introducing gradual improvements. Another challenge lies in clearly communicating the benefits of human-machine interaction, as emphasized by a participant: *"the benefit of human-machine interaction needs to be clear towards the user"* (S1) to ensure engagement.

4.2 Data management & quality

The aggregate dimension 'data management & quality' incorporates insights regarding the topic of data quality within the shop floor area. It also stresses the need for data enrichment and interpretation, adding context to raw data to generate actionable insights for industrial business problems.

The study identifies challenges within the 2nd order themes 'data centralization across systems' and 'quality data in one place'. A key challenge lies in centralizing data from diverse systems, including both sensor-generated shop floor data and derived insights, into a single location for broader utilization. The study highlights the need to ensure data specificity, reliability, and relevance to enable accurate conclusions, which may require data-cleaning processes before centralization. Participants emphasized these challenges, with one interviewee noting that *"different data sources need to be unified"* (I3), while another stressed that *"data sets with high quality are important for process mining"* (I4). These findings underscore the complexities in achieving effective data centralization and maintaining data quality in process mining implementations.

The study identifies critical issues within the 2nd order themes 'contextualizing data information' and 'real-time data processing & insights'. A key challenge lies in integrating diverse data sources into existing streams, particularly in connecting business context and manufacturing process information for effective root cause determination. This is especially crucial for operating sequences involving human operations. Another significant hurdle emerges in real-time data processing for process mining, questioning its ability to keep pace with production processes. These challenges are highlighted by interviewees, with one emphasizing that *"contextual information is key as not everything is captured in current production spaces"* (A1), and another noting that *"real-time process mining is desirable, but real-time data processing remains challenging"* (P2).

4.3 Digitalization & technology advancements

The aggregate dimension of 'digitalization & technology advancements' emerged as a central theme. This dimension covers future developments in process mining and shop floor applications, emphasizing the importance of digitalization across industries. These aspects, crucial for process mining, are relevant to many digital solutions but are especially vital for advancing process mining in manufacturing.

The 2nd order theme, 'need for digitalization in production,' highlights that process mining can only be effective with digitized processes. Our research findings emphasize the importance of end-to-end digitization, which presents a significant challenge in manufacturing environments. Achieving this comprehensive digital transformation requires substantial investments in technology, training, and infrastructure. As one interviewee noted, illustrating the extent of digitization needed, *"every little parameter change is important to know"* (P3). At the same time, another stressed the prerequisite nature of digitization, stating *"manufacturing must be more digitized before using process mining"* (I5).

The study identifies opportunities and challenges within the 2nd order theme 'Future of AI' for process mining. A key area of focus is the potential role of AI in enabling non-experts to analyze data more effectively, presenting challenges in democratizing data analysis. The study highlights the potential of machine learning in identifying clusters within large data sets. Participants expressed optimism about AI's potential, with one interviewee stating that *"AI will help to improve the workplace"* (I6) and another noting that *"the potential for large language models is considerable"* (P2).

4.4 Process efficiency & optimization

A further aggregate dimension that emerged from the data analysis was 'process efficiency & optimization'. This dimension encapsulates the value proposition of process mining as a means of streamlining and enhancing the performance of business processes, providing insights into how organizations can identify inefficiencies, bottlenecks, and potential areas for improvement within their processes.

The 2nd order theme, 'Efficiency & Optimization Challenges in Process Mining', captures productivity problems worked on with process mining. Participants stated that increasing efficiency is a critical goal in producing industries, which can be achieved due to process mining. An interviewee highlighted that with process mining *"increased profits due to better management and planning"* (I4) are possible.

The study identifies challenges within the 2nd order themes 'Process Mining for Enhancing Visibility & Transparency'. A key hurdle lies in leveraging process mining to uncover previously hidden insights into company processes through process discovery and relationship mapping between objects and process steps. The study highlights the complexity of using process mining to *"link different processes and showing problems occurring from them"* (I5) while also *"knowing where everything is"* (I6). Another significant challenge emerges in the 2nd order theme 'Identifying & Improving Bottlenecks', which captures how to effectively identify root causes and facilitate early detection of shop floor problems.

4.5 Production & supply chain complexity

The aggregate dimension 'production & supply chain complexity' encompasses themes related to maintaining a resilient, well-functioning, and uninterrupted supply chain. Additionally, it highlights how the diversity and uniqueness of production processes complicate the ease of use for process mining applications.

Despite the shop floor focus, the study identifies challenges within second-order themes related to supply chain management, including 'complexity of tracking supply chain', 'uninterrupted supply chain', and 'unflexible supply chains'. A key challenge lies in ensuring the timely availability of correct components for production, while end-to-end supply chain tracking remains difficult due to disconnected data systems. Participants emphasized these challenges, with one noting that the *"supply chain environment is complex with many people involved"* (P1) and another observing that *"problems usually come from the supply chain and not the production"* (A2).

The study identifies challenges within the 2nd order themes 'variance of production processes' and 'complexity of production & planning'. A key challenge lies in developing individual approaches for manufacturing lines while maintaining interconnected shop floor processes. Participants emphasized these challenges, with one noting that the *"shop floor is highly complex for process mining"* (I4) and another observing that *"production data variability is inherent even within the same factory for different production lines"* (I7).

In conclusion, based on 22 interviews, our study revealed different challenges, such as the need for inter-organizational and inter-departmental communication and the importance of end-to-end data capturing and centralization while highlighting the complexities of production and supply chain management, each of which must be addressed to effectively implement process mining on the shop floor.

5 Discussion

This section examines the recognized challenges, connects them with existing research, and explores potential solutions that could make the implementation of process mining on the shop floor easier.

Among our findings, a significant cluster of mentions concerns data, primarily falling into the aggregate dimension 'data management & quality', with some data gathering points in the 'digitalization & technology advancements' dimension. Building upon Netto et al.'s [12] findings, IT infrastructure limitations were not prominently mentioned in our study. Our research instead highlights the frequent mention of real-time data streaming as an enabler for expanding process mining into new use cases requiring prompt reactions, aligning with Reinkemeyer's [17] observations on dynamic process mining applications. The findings reveal challenges in implementing process mining within organizations, echoing Martin et al.'s [10] findings on the importance of team composition and requisite skills. Our study aligns with Zimmermann et al.'s findings, emphasizing that training and ongoing education within organizations and educational institutions are crucial for successfully implementing new technologies [25].

Implementing process mining on the shop floor necessitates a comprehensive change management strategy to effectively engage all stakeholders, particularly those directly impacted by the technology. This approach addresses workers' fears of job loss due to technology, promoting user engagement. This finding aligns with Bala et al.'s emphasis on involving users early in the process when introducing process mining and communicating the benefits of the technology [2]. Our findings reinforce Reinkemeyer's [17] assertion that centralizing both structured and unstructured data in one place is pivotal for successful implementation. Furthermore, we underscore the importance of reliable data input for process mining, echoing the sentiments of Hofstede et al. [23], to ensure the accuracy and reliability of analytical outcomes. This imperative extends beyond implementing organizations to encompass software and cloud providers, who are crucial in lowering the entry barriers for process mining on the shop floor.

To summarize, we discovered that various areas are essential to successfully implement process mining on the shop floor. This exploratory study has identified initial patterns, suggesting the need for broader research across diverse industries, personas, and company sizes to validate and extend these findings. We encourage future research to broaden its focus beyond technological solutions, considering the organizational and human implications, and to explore the emerging field of "Process Science" [5].

Our study has limitations typical of interview-based research. Participants might have been influenced by recency biases when reporting on the benefits and challenges of process mining. In addition, desirability bias can potentially emerge in interview studies. Researcher bias may have influenced data collection and analysis, potentially affecting the study's outcomes. Our findings from interviews with recommended participants, primarily from the German market, offer valuable insights but may not be exhaustive due to sampling biases. To enhance validity, future research should consider methodological triangulation to corroborate findings and mitigate potential biases inherent in single-method approaches.

6 Conclusion

Based on 22 interviews with representatives from academia, manufacturing and process mining experts, shop floor workers, and production managers, we identified five core aggregated dimensions around process mining on the shop floor. Our research highlights the importance of organizational and human factors as well as data management and quality for a successful process mining implementation on the shop floor. Successful implementations yield process efficiency and optimization and go hand-in-hand with digitalization and technological advancements in manufacturing companies. Meanwhile, the complex and varied nature of production and supply chain is a challenge for successfully applying process mining at scale.

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