Combining value stream mapping and process mining in production: a systematic literature review

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Abstract

Value stream mapping is a widely used and proven method in lean production for gaining transparency into the current state of a production process. To reduce the inefficiency of manually mapping increasingly complex production systems, the growing availability of digital shop floor data offers the potential to digitalize and automate value stream mapping. Approaches based on process mining are considered particularly promising. Therefore, this review article aims to identify, compare, and synthesize existing approaches that combine value stream mapping and process mining in production based on a systematic literature review according to PRISMA 2020. The review includes 21 out of 2,682 initially identified records. They are analyzed regarding their metadata, content, and process mining-specific data items. The results are discussed in terms of research gaps and future research directions. While the reviewed approaches offer valuable practical benefits, especially for in-depth analyses, most records present just concepts or case studies without systematic tool support. Further research on novel process mining techniques dedicated to value stream mapping is needed for true integration of value stream mapping and process mining. This review contributes to this effort by identifying open research gaps and suggesting four future research directions.

Keywords: Value stream mapping; process mining; lean production; digitalization; systematic literature review; PRISMA 2020

1 Introduction

Value stream mapping is a well-established and proven method in lean production. By depicting the actual production processes as comprehensively as possible, it creates the necessary transparency to identify waste (e.g., overproduction, waiting, and inventory) and further potential for improvement [1]. However, the analog nature of traditional value stream mapping poses problems, particularly as production systems grow more flexible and complex. Its manual snapshot of a single representative, scaled for an entire product family, disregards dynamics and heterogeneity [2]. Current research on the digitalization and automation of value stream mapping addresses these problems. The combination of value stream mapping and process mining techniques is considered particularly promising [3].

Process mining is a relatively young discipline bridging the gap between process and data science. Its techniques leverage readily available event data to discover, monitor, and improve real processes [4]. With the advent of digital transformation and Industry 4.0, such event data is also becoming increasingly available in production [5]. Leveraging this data by combining process mining techniques with the proven method of value stream mapping could revolutionize lean production management.

Both value stream mapping and process mining share the common objective of evidence-based process improvement. They make process flows transparent in order to identify and eliminate waste. At the same time, they complement each other. Value stream mapping provides a top-down, systematically simplified, and aggregated, end-to-end view of a segmented product family, along with system-level metrics [1]. Conversely, process mining reconstructs bottom-up instance-level executions from time-stamped events, capturing variability and dynamics [4]. Combining them can leverage their commonalities and complementary strengths.

However, obtaining an overview of the current state of research on combining value stream mapping and process mining in production presents a challenge. While literature reviews by Horsthofer-Rauch et al. [3] as well as Wollert and Behrendt [6] provide first insights, both only consider work before 2022. Additionally, these reviews lack thorough comparisons and discussions of the included records. Missing transparency regarding existing approaches leads to isolated solutions, duplicated work, and undiscovered research gaps.

This review article aims to identify, compare, and synthesize existing approaches that combine value stream mapping and process mining in production. The objective is to provide a comprehensive overview of the current state of research in this field. Therefore, a systematic literature review was conducted according to the PRISMA 2020 guidelines [7]. Additionally, research gaps are identified, and future research directions are suggested. Thus, this review article contributes to consolidating existing approaches and advancing research activities in this field.

The remaining article is structured as follows. Section 2 provides the necessary background on value stream mapping and process mining. Section 3 describes the methodology used for the systematic literature review. Section 4 presents the results, which include 21 records that combine value stream mapping and process mining in production. Section 5 discusses the results and identifies needs for further research. Section 6 concludes this review article.

2 Background

Before presenting the actual literature review, the following subsections introduce the necessary background on value stream mapping and process mining.

2.1 Value stream mapping

Value stream mapping is one of the most important and prevalent methods in lean production. It is part of the first phase of the overall value stream method and systematically helps “learning to see” the current state of a selected value stream [1, 8]. The value stream map aims to depict the end-to-end production process within a plant “as comprehensively as possible” [1]. Therefore, it uses a largely standardized set of symbols and key figures tailored to lean production process improvements [1, 9]. Fig. 1 shows an illustrative example of a value stream mapping with the main symbols: customer (house), external logistics (truck and white arrow), storage and material flow (triangle and striped arrow), production processes (rectangle), supplier (factory shed roof), and information flow with arrows marked by different information types (e.g., document, list, data set). The data boxes below the main symbols contain average key values, such as operation time, that are collected directly from the shop floor. They also contain key figures, such as cycle time, that are calculated based on key values. These two levels of abstraction have to be met by an automation data acquisition and calculation.

A value stream is traditionally mapped manually with pen and paper during a production tour. Operation and processing times are measured with a stopwatch.

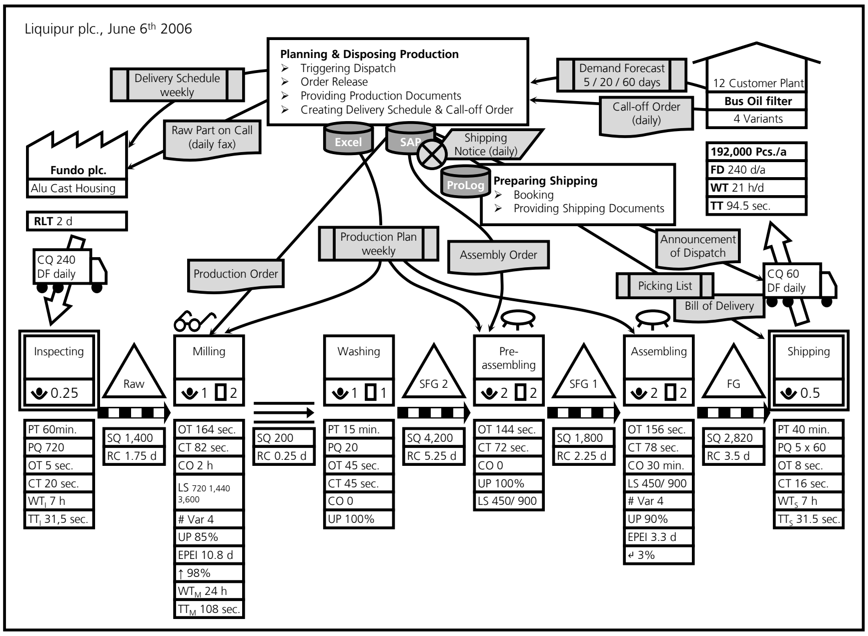

Fig. 1 Example of a value stream mapping at Liquipur by Erlach [1]

Stocks are counted on site. Other key figures are collected through interviews with the operators who carry out the respective activities. This can be traced back to the origins of the value stream method in the Toyota Production System of the 1950s. The idea is to record actual behavior on the shop floor instead of using inaccurate standard values.

To reduce manual mapping effort, targeted simplifications are made. Assuming serial production characteristics, each value stream is mapped for one representative product variant and scaled for the entire product family. Additionally, only the material flows of the main components are typically considered [1]. While the assumption of serial production characteristics was generally valid during the eras of mass production and mass customization, production systems nowadays are often more complex. They feature greater product variety and smaller production volumes per variant [10].

Digital transformation of production—also known as Industry 4.0—has the potential to revolutionize traditional methods of lean production, such as value stream mapping. Its advent has led to an increase in the availability of digital feedback data that describes actual behavior on the shop floor. Approaches that digitalize value stream mapping aim to use this data to discover the value stream map mostly automatically. This promises to reduce effort, especially when updating the mapping. It also provides a more comprehensive description of complex production systems through a data-driven bottom-up recording of the value stream. Process mining-based approaches are seen as particularly promising [3].

2.2 Process mining

Process mining is a rapidly evolving and disseminating research discipline. Its mission is to bridge the gap between process science and data science by discovering, monitoring, and improving real processes based on digital event data [4]. As with value stream mapping, process discovery techniques seek to model processes as they actually are. The process model is automatically inferred based on the behavior observed in the event data, taking the perspective of a selected case identifier. The process is usually modeled using a directly-follows graph (DFG), a business process model and notation (BPMN), or a Petri net. To obtain a fully integrated model, the model can be extended with additional perspectives and key figures [4].

Recent advancements in object-centric process mining go beyond the traditional case-centric approaches. In reality, cases are not executed in isolation and involve different types of interrelated objects. Often, multiple objects are involved in an event [11]. In the production context, for instance, resources transform input items into output items according to an order. Object-centric process mining considers multiple object types (e.g., resource, item, and order) and events involving any number of objects. This allows for a more comprehensive and holistic modeling of complex processes, such as value streams in production.

3 Methodology

The research method used in this article is a systematic literature review. A systematic literature review is a “systematic, explicit, and reproducible method for identifying, evaluating, and synthesizing the existing body of completed and recorded work produced by researchers, scholars, and practitioners" [12]. It provides a firm foundation for advancing knowledge in a particular research field, both by closing in on areas where there exists a plethora of research and by uncovering areas where research is needed [13].

This article follows the structure of the preferred reporting items for systematic reviews and meta-analyses PRISMA 2020 [7], a widely used guideline for systematic literature reviews. Although this guideline was initially developed for health-related interventions, most of its 27 recommended reporting items are applicable to other disciplines, such as production engineering. The application of PRISMA 2020 in this article should lead to a more transparent, complete, and accurate reporting of the systematic review conducted [14].

The rest of this section provides a more detailed explanation of this literature review's methodological approach, based on relevant PRISMA 2020 items.

3.1 Eligibility criteria

The eligibility criteria specify the characteristics that determine which research contributions are included in the systematic review and which are excluded [15]. First, this systematic literature review conducted an exhaustive search without applying any additional inclusion criteria. No period was specified because the combination of value stream mapping and process mining is a relatively new research field. Second, the exclusion criteria for screening the identified research contributions were as follows:

- EC1. Language other than English or German
- EC2. Publication types other than journal articles, conference articles, contributions to edited volumes, monographs, or dissertations
- EC3. Irrelevant context to at least one of the main aspects of this review: value stream mapping, process mining, and production
- EC4. Records that do not present an approach that combines value stream mapping and process mining
- EC5. Secondary sources that only cite an approach combining value stream mapping and process mining, as presented in another publication

3.2 Information sources

Searching multiple information sources—recommended in the PRISMA-S guideline—maximizes the likelihood of identifying relevant contributions [16]. To conduct an exhaustive search for existing research contributions combining value stream mapping and process mining in production, the following nine information sources were searched:

- Publisher databases: ScienceDirect; IEEE Xplore; SpringerLink
- Literature databases: Scopus; Web of Science; Dimensions
- Special search engines: Google Scholar; BASE; Fraunhofer eLib

3.3 Search strategy

The search string used to identify the records from the information sources addresses the three main aspects of this review: the two main approaches to be combined—value stream mapping and process mining—as well as the application context of production. For each aspect, keywords and their synonyms in English and German were chosen, resulting in the following search string:

(value_stream OR Wertstrom*) AND "process mining" AND (produ?tion OR manufacturing OR shop_floor)

For information sources that do not support truncation or wildcards, the following alternative search string was used:

("value stream" OR Wertstrom) AND "process mining" AND (production OR Produktion OR manufacturing OR "shop floor" OR shopfloor OR shop-floor)

If selectable, the search was within all fields of the information source.

3.4 Selection process

Once the records were identified from the information sources, a three-stage selection process was conducted by one reviewer. The first stage—before screening—was to remove duplicates within or between the different information sources. Another reason for removing records before screening was that they could not be found. The link was broken, and the available metadata produced no relevant hits in online searches. The second stage was to screen the titles and abstracts. Records were excluded according to the defined exclusion criteria: language (EC1), publication type (EC2), and irrelevant context (EC3). All remaining records have been retrieved. The third stage was a full text review. Records were excluded if they did not present an approach combining value stream mapping and process mining (EC4) or were only a secondary source (EC5). In the latter case, all the primary sources referred to were already included in the identified records.

3.5 Data collection process, data items, and synthesis methods

To compare and synthesize the included records, one reviewer collected data from each record. This data collection process was guided by an iteratively adapted protocol. The final version of the protocol includes the following data items:

- Metadata: publication date; language; publication type; affiliations
- Content: objective; main contributions
- Process mining: data source; case; software; process model

The collected data items from all protocols were then summarized and organized into a literature review matrix [17]. Compiling such a matrix makes the transition from an author-centric perspective to a concept-centric perspective for comparison and synthesis of the included records [13].

4 Results

The following presents the results of the systematic literature review, which covers the selection process, a descriptive analysis of the included records, a synthesis of these records, and a more detailed analysis of the process mining-related data items.

4.1 Application of the selection process

Applying the methodology described, the PRISMA 2020 flow diagram in Fig. 2 illustrates the different phases of the literature review conducted. In the first phase, the search in the nine information sources on May 17, 2025, identified a total of 2,682 records. Notably, Dimensions and Google Scholar together accounted for about three-quarters of these records. In contrast, Web of Science, IEEE Xplore, and BASE together accounted for only about one percent. Before screening, a total of 1,006 records were removed. 996 records were identified as duplicates. Of these, 124 records were duplicates found within the same information source, while 872 records were duplicates identified by multiple information sources. Ten records could not be found. The link was broken, and the available metadata yielded no relevant results during online search. In the second phase, the remaining 1,676 records were screened. After screening the metadata, title, and abstract, a total of 1,512 records were excluded. 257 records were not in English or German (EC1). 669 records were excluded due to their publication type (EC2), e.g., entire collective volumes, conference proceedings, or master theses. 586 records had an irrelevant context (EC3). For the remaining 164 records, the full texts were retrieved and screened. A total of 143 records were excluded. 95 records do not combine value stream mapping and process mining (EC4). 48 records are only secondary sources (EC5). All their relevant primary sources were already included in the initially identified record. The remaining 21 records (Table 1) were included in the review.

Fig. 3 shows the performance of the information sources in finding the included records. The left side of the figure shows the percentage of included records covered by the identified records from each information source. None of the nine information sources identified all 21 included records. This underscores the importance of searching multiple information sources. Google Scholar identified most of the included records. In particular, it identified three of the four records included that were only identified by one of the nine information sources. However, Google Scholar, along with Dimensions and ScienceDirect, also had one of the lowest percentages of included to identified records.

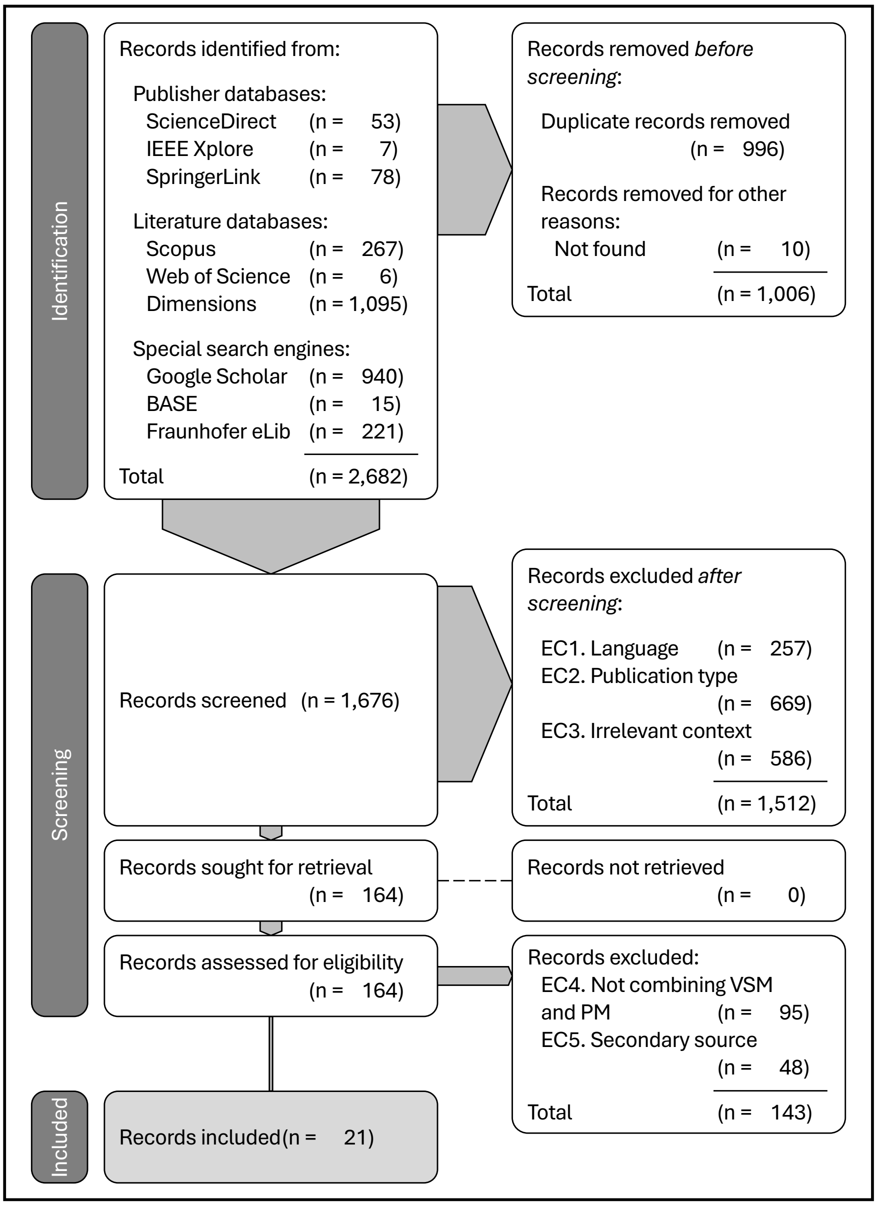

Fig. 2 PRISMA 2020 flow diagram illustrating the different phases of the literature review conducted based on Page et al. [7]

Table 1 Included records and their metadata for the descriptive analysis

Ref.	Publication	Language	Publication type	Affiliations
[18]	07.01.2019	en	journal article	TU Munich; BMW AG
[19]	01.06.2019	de	monograph	Contales; Heidelberger Druckmaschinen AG; DHBW Mannheim
[20]	27.06.2019	de	journal article	Fraunhofer IGCV
[21]	23.09.2019	de	journal article	SALT Solutions AG
[22]	17.12.2019	de	journal article	TU Darmstadt
[23]	20.03.2020	en	conference article	TU Leoben
[24]	25.09.2020	en	conference article	TU Darmstadt
[25]	12.05.2021	en	conference article	PUCPR
[26]	07.06.2021	en	journal article	University of Pannonia; Vietnam Maritime University; Sunstone-RTLS Ltd.
[27]	19.09.2021	de	journal article	TU Munich
[28]	08.02.2022	en	PhD thesis	TU Munich
[29]	16.02.2022	en	journal article	Brno University of Technology; University of Applied Sciences Emden/Leer; Honeywell
[30]	01.03.2022	en	journal article	RWTH Aachen University; ITA Academy GMBH
[31]	21.09.2022	en	conference article	Magdeburg-Stendal University of Applied Sciences
[32]	01.09.2023	de	PhD thesis	TU Darmstadt
[33]	23.11.2023	en	conference article	University of Technology Sydney
[34]	27.03.2024	en	journal article	TU Munich; Celonis SE; HAWE Hydraulik SE
[35]	03.04.2024	en	conference article	Magdeburg-Stendal University of Applied Sciences
[36]	11.07.2024	en	conference article	Magdeburg-Stendal University of Applied Sciences
[37]	16.10.2024	en	journal article	Islamic Azad University; Iran University of Science and Technology
[38]	20.10.2024	de	journal article	Bross Consulting GmbH; Landshut University of Applied Sciences

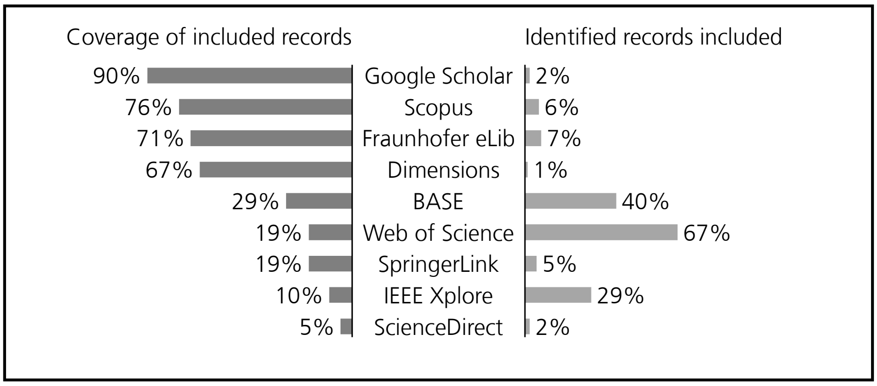

Fig. 3 Performance of the information sources

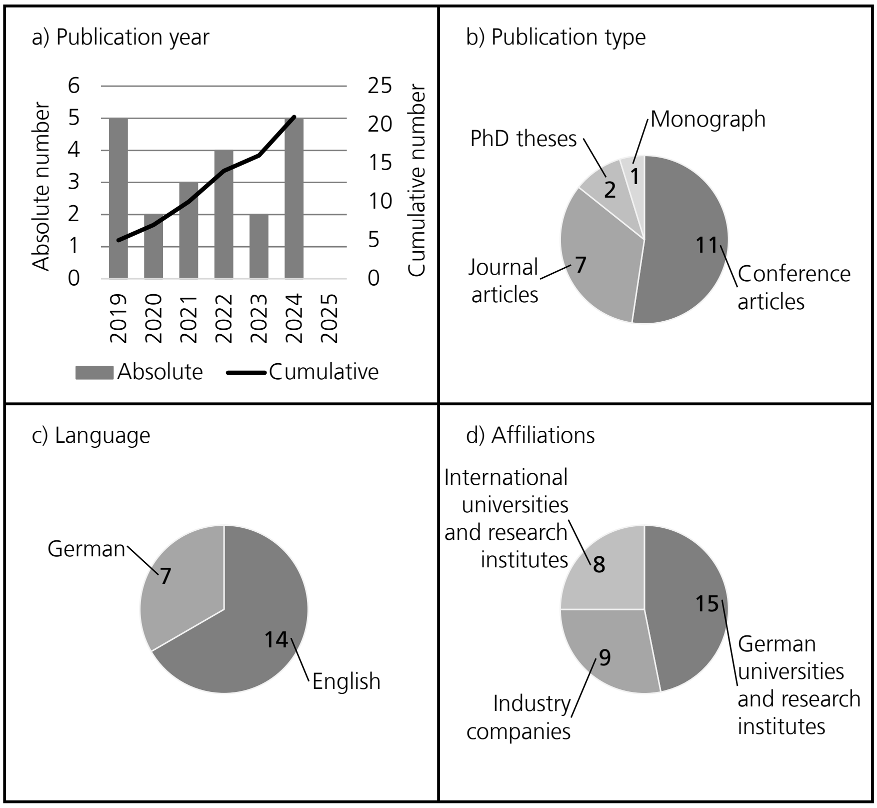

Fig. 4 Descriptive analysis of the included records: a) absolute and cumulative publication years; b) distribution by publication type; c) distribution by language; d) distribution of affiliations

4.2 Descriptive analysis of included records

For the 21 included records, first, a descriptive analysis of their metadata (Table 1) was conducted. Fig. 4 a) shows that the first records were published in 2019, indicating that the combination of value stream mapping and process mining in production is a relatively recent approach. The cumulative representation suggests that the number of records remained relatively constant over the subsequent years. The peaks in absolute representation in 2019 and 2024, with five records, once again highlight the importance of an up-to-date overview of the current state of research on combining value stream mapping and process mining in production.

Fig. 4 b) shows that most of the included records are conference and journal articles, which tend to reflect the current state of research more directly. This may also indicate that it is a relatively young and rapidly evolving research area. However, two PhD theses and one monograph are also included.

Fig. 4 c) shows that most of the included records are in English. However, German-language records also account for a substantial portion, amounting to one-third of the total. This relevance to include German-language records for the context of process mining-enabled value stream mapping was also identified by Horsthofer-Rauch et al. [34].

Fig. 4 d) shows the distribution of affiliations of the included records' authors. Each affiliation was counted only once per included record. In this case, German universities and research institutes also have a larger share than all other international universities and research institutes combined. Most affiliations are with the Technical University of Munich (4), the Technical University of Darmstadt, and the Magdeburg-Stendal University of Applied Sciences (3 each). Furthermore, more than a quarter of the affiliations are with industry companies, which indicates a high level of application relevance.

In addition to the metadata, the descriptive analysis also examined the citation relationships among the included records. Fig. 5 shows a corresponding overview. When analyzing this overview, it is essential to consider the time lag between submitting a paper, book, or thesis and its publication. Nonetheless, most of the included records cite only one or no other of the included records. Only Urnauer et al. [24], Horsthofer-Rauch, Vernim, and Reinhart [27], Urnauer [32], as well as Horsthofer-Rauch et al. [34] cite a significant portion of the previously published included records. On the other hand, Knoll, Reinhart, and Prüglmeier [18]—the oldest of the included records—is the most frequently cited both in absolute terms and relative to the total number of subsequently published included records.

4.3 Synthesis of included records

To compare and synthesize the included records, the records were first analyzed based on their content. Some of the included records have partially overlapping authors, and their content builds upon each other. Therefore, these records are grouped. Three such groups were identified:

1. Knoll, Reinhart, and Prüglmeier [18]; Knoll [28]

2. Urnauer and Metternich [22]; Urnauer et al. [24]; Urnauer [32]
3. Horsthofer-Rauch, Vernim, and Reinhart [27]; Horsthofer-Rauch et al. [34]

These groups also represent the most advanced approaches that combine value stream analysis and process mining in production. The other included records represent either conceptual/initial approaches or partial aspects. Table 2 organizes the individual included records into these categories and summarizes each's objective and main contribution. A summary of the main contents within each category is provided below.

cited by	Knoll, Reinhart, and Prüglmeier 2019	Lindner and Richter 2019	Ziegler, Braunreuther, and Reinhart 2019	Klenk 2019	Urnauer and Metternich 2019	Mertens, Bernerstätter, and Biedermann 2020	Urnauer et al. 2021	Nawcki et al. 2021	Tran, Ruppert, and Abonyi 2021	Horsthofer-Rauch, Vernim, and Reinhart 2021	Knoll 2021	Rudnitckaia et al. 2022	Schuh et al. 2022	Wollert and Behrendt 2022a	Urnauer 2023	Tomidei et al. 2023	Horsthofer-Rauch et al. 2024	Wollert and Behrendt 2024	Wollert et al. 2024	Khakpour, Ebrahimi, and Seyed-Hosseini 2025	Bross, Götz, and Wunderlich 2024
Knoll, Reinhart, and Prüglmeier 2019																					
Lindner and Richter 2019																					
Ziegler, Braunreuther, and Reinhart 2019																					
Klenk 2019																					
Urnauer and Metternich 2019			X																		
Mertens, Bernerstätter, and Biedermann 2020																					
Urnauer et al. 2021	X		X	X	X																
Nawcki et al. 2021	X																				
Tran, Ruppert, and Abonyi 2021	X																				
Horsthofer-Rauch, Vernim, and Reinhart 2021	X		X	X	X		X														
Knoll 2021	X																				
Rudnitckaia et al. 2022	X																				
Schuh et al. 2022	X																				
Wollert and Behrendt 2022a									X												
Urnauer 2023	X	X	X	X	X	X	X	X			X										
Tomidei et al. 2023	X																				
Horsthofer-Rauch et al. 2024	X		X	X	X		X	X		X		X									
Wollert and Behrendt 2024						X								X							
Wollert et al. 2024														X							
Khakpour, Ebrahimi, and Seyed-Hosseini 2025																					
Bross, Götz, and Wunderlich 2024	X										X										
∑	11	1	5	4	4	2	3	2	1	1	2	1	-	2	-	-	-	-	-	-	-

Fig. 5 Citation relationships among included records

Table 2 Categorization of the included records with their objective and main contribution

	Ref.	Objective	Main contribution
Conceptual/initial approaches	[19]	Introducing a practical application of process mining software in value stream mapping projects	A project approach that combines the application of process mining software, an optimization workshop with the team, and the sustainable implementation of agreed-upon measures
	[20]	Motivating the use of process mining for dynamic value stream mapping	A demonstration of the potential of process mining for dynamic value stream mapping
	[21]	Developing a concept to analyze physical and IT-based processes in interaction and improve the overall production system	A concept that extends traditional value stream mapping by using process mining to automatically model IT system-based processes
	[23]	Developing a method that combines traditional value stream mapping and process mining to address challenges in order production	A demonstration that process mining can help to identify the most common material flows in order-production
	[25]	Understanding value stream mapping and empirically comparing it with process mining	A demonstration that process mining can increment value stream mapping
Advanced approaches	[18]	Developing a methodology to enable value stream mapping within internal logistics for a mixed-model assembly line using process mining	A multidimensional process mining methodology for practitioners to enable a continuous recording, evaluation, and waste analysis of each individual part and process within internal logistics
	[28]	Enabling an effective and efficient application of value stream mapping in internal logistics using process mining	A methodology for value stream mapping in internal logistics using process mining, including an internal logistics ontology, automated event log creation/ enrichment, and practical guidelines
	[22]	Developing a digital value stream method that uses process mining to address the limitations of traditional value stream analysis in handling the complexity of modern production systems	A concept that focuses on a data-assisted value stream analysis, extending traditional value stream mapping by using process mining to enable the analysis of complex value streams

Table 2 Categorization of the included records with their objective and main contribution (continued)

	Ref.	Objective	Main contribution
Advanced approaches (continued)	[24]	Developing a framework for a data-assisted value stream method	A framework for a continuously integrated data assistance within the value stream method, including a team structure, best practice procedures, and requirements
	[32]	Further developing the value stream method to make it more effective through the use of data analytics	A procedure model for integrating selected data analytics functions into the value stream method and its elaboration
	[27]	Developing a concept for the digitalization of value stream mapping and a simultaneous integration of sustainability aspects	A concept for sustainability-focused digital value stream mapping by integrating process mining techniques
	[34]	Developing a process-mining-based sustainability-integrated value stream mapping to enable continuous analysis of all product value streams in practice	A framework for the implementation of process mining-based sustainability-integrated value stream mapping, including technical details
Partial aspects	[26]	Highlighting how data provided by indoor positioning systems can be utilized for Lean-based process improvement of flexible manufacturing systems	A PDCA-cycle-based methodology using indoor positioning system data and process mining for dynamic value stream mapping
	[29]	Screening process mining and value stream techniques on digital manufacturing processes for process modeling and bottleneck analysis	An approach that combines process mining for process modeling and bottleneck analysis with value stream techniques for analysis and validation of the value streams
	[30]	Developing a methodology to describe process performance using process mining in end-to-end order processing of manufacturing companies as an alternative to traditional methods, such as value stream design	A six-step methodology for the application of process mining in end-to-end order processing with multiple order types

Table 2 Categorization of the included records with their objective and main contribution (continued)

	Ref.	Objective	Main contribution
Partial aspects (continued)	[31]	Providing a conceptual data framework to automate manufacturing process mapping in the context of value stream management by leveraging ERP system data	A data framework that links traditional value stream management key figures to ERP business and data objects, enabling their automated derivation and calculation
	[33]	Developing a method for identifying key value streams in complex, high-variety manufacturing environments by leveraging production data through process mining and machine learning techniques	A method for identifying product families by trace clustering and associated key value streams by process discovery from production data
	[35]	Investigating a digital twin concept to improve the value stream methodology	A concept for a digital value stream twin with focus on the manufacturing process
	[36]	Investigating the application of a digital value stream twin within learning factory environments to enhance operational optimization and transparency	A concept for a digital value stream twin for a FESTO learning factory that captures real-time data and enables dynamic visualization, monitoring, and control of the value stream performance
	[37]	Developing a method that integrates process mining with value stream mapping to enable dynamic, real-time mapping, analysis, and improvement of manufacturing processes	A method for lean process mining with three main phases: as-realized process state, improvement strategies, and reengineered process state
	[38]	Developing a method that supports manufacturing companies to successfully implement process mining in practice	A method for implementing process mining in intralogistics, including: process initialization, the extraction and preparation of the data, the execution of analyses, the interpretation of the results, and the derivation of measures

4.3.1 Conceptual/initial approaches

Lindner and Richter [19], Ziegler, Braunreuther, and Reinhart [20], as well as Klenk [21] are among the oldest included records. All three highlight the limitations of traditional value stream mapping—such as its static and subjective nature—and advocate for using process mining software to enable objective, data-driven, and dynamic value stream mapping. While Lindner and Richter [19] focus on practical application, Ziegler, Braunreuther, and Reinhart [20] stress the ability to increase transparency, even in complex value streams. Klenk [21], on the other hand, focuses on analyzing physical and IT-based processes in interaction. Mertens, Bernerstätter, and Biedermann [23], as well as Nawcki et al. [25] conduct case studies comparing value stream mapping and process mining. Based on their findings, they both conclude that value stream mapping and process mining complement each other.

4.3.2 Advanced approaches

Knoll [28] and Urnauer [32] are the included PhD theses. They can be considered representative of the first two groups of records that were initially identified. Knoll [28] uses multidimensional process mining to enable value stream mapping for internal logistics. Urnauer [32] proposes a particular set of data analytics functions to assist in the analysis and design of value streams, including process mining for value stream mapping. Both approaches are characterized by their advanced nature, having been demonstrated in a few relevant environments. Horsthofer-Rauch et al. [34] represent the most recent record of group three. It elaborates the previously defined framework for implementing process-mining-based sustainability-integrated value stream mapping [27]. The implementation within the Celonis platform, as well as its demonstration in a relevant industrial environment, are indicative of its advanced nature.

4.3.3 Partial aspects

The remaining records focus on specific, partial aspects. Tran, Ruppert, and Abonyi [26] as well as Wollert and Behrendt [31] focus on data acquisition. Tran, Ruppert, and Abonyi [26] use indoor positioning systems, while Wollert and Behrendt [31] link value stream mapping key figures to enterprise resource planning business and data objects. Wollert and Behrendt [35] as well as Wollert et al. [36] investigate bidirectionally connected digital value stream twins. Tomidei et al. [33] focus on extracting key value streams using process mining and machine learning. In the context of traditional value stream mapping, these key value streams represent product families. Rudnitckaia et al. [29] as well as Khakpour, Ebrahimi, and Seyed-Hosseini [37] focus on the analysis of bottlenecks and wastes within the discovered processes. Schuh et al. [30] as well as Bross, Götz, and Wunderlich [38] focus on the end-to-end modeling of production and logistics processes. Because there is often no consistent case identifier, they propose object-centric process mining approaches.

4.4 Analysis of process mining data items

Following the comparison and synthesis of the main content of the included records, a more detailed analysis of the collected data items related to process mining is presented below.

Most of the included records also describe an example application within a use case. Table 3 shows the corresponding data items related to process mining.

Table 3 Collected data items related to process mining

	Ref.	Data source	Case	Software	Process model
Conceptual/ initial approaches	[19]	e.g., ERP or CRM	production order	LANA Process Mining	DFG
	[20]	e.g., ERP, MES or SCADA	N/A	ProM	BPMN
	[21]	e.g., ERP or MES	e.g., order or material movements	N/A	extended DFG with simplified VSM symbols
	[23]	N/A	order	N/A	DFG
	[25]	quality information systems	N/A	Disco	DFG
Advanced approaches	[18]	WMS	smallest unit load	Disco	DFG
	[28]	WMS or ERP	smallest unit load	ProM	DFG
	[22]	N/A	e.g., item or order	N/A	N/A
	[24]	e.g., ERP or MES	N/A	N/A	N/A
	[32]	e.g., ERP or MES	order	PM4Py	DFG
	[27]	N/A	N/A	N/A	N/A
	[34]	e.g., ERP	N/A	Celonis platform	DFG
Partial aspects	[26]	indoor positioning system	order (paired with transportation cart)	Disco	DFG

Table 3 Collected data items related to process mining (continued)

	Ref.	Data source	Case	Software	Process model
Partial aspects (continued)	[29]	MES	e.g., item or resource	ProM and Disco	e.g., DFG, Petri net, object-centric Petri net, or BPMN
	[30]	CRM, ERP, or MES	object-centric: order types	ProM	BPMN or object-centric Petri net
	[31]	ERP	N/A	N/A	N/A
	[33]	N/A	item	RapidProM	BPMN
	[35]	ERP	N/A	N/A	N/A
	[36]	MES	N/A	N/A	N/A
	[37]	IIoT sensors	item	Celonis platform	DFG
	[38]	WMS or ERP	object-centric: e.g., item types or unit load	N/A	N/A

4.4.1 Data sources

Most approaches use existing information systems, such as enterprise resource planning (ERP) systems, manufacturing execution systems (MES), warehouse management systems (WMS), and customer relationship management (CRM) systems. However, some approaches also collect data, such as through indoor positioning systems [26] or industrial internet of things (IIoT) sensors [37].

4.4.2 Cases

With respect to the case definition for process discovery, considerable variation is evident among the included records. Some approaches focus on directly tracking items throughout the production process, as in traditional value stream mapping. However, included records from the field of logistics emphasize that tracking individual items—such as single screws—is often not technically or economically feasible in practice [28, 38]. Consequently, these approaches typically use unit loads as cases. By contrast, approaches that use existing ERP or MES data mostly define cases based on orders.

4.4.3 Software and process models

The example applications of the included records used general-purpose process mining software (i.e., Disco, ProM, Celonis platform, LANA Process Mining, PM4Py) for process discovery. The discovered process model is mostly represented as a directly-follows graph (DFG). Other examples use the business process model and notation (BPMN), Petri nets, or object-centric representations. Only a few records consider using traditional value stream mapping symbols [20, 21], but stay on the conceptual level.

5 Discussion

The reviewed approaches are the first promising steps toward combining value stream mapping and process mining in production. They demonstrate how process mining techniques can help overcome the limitations of traditional value stream mapping in today's increasingly flexible and complex production systems by offering data-driven depth. However, most records only present a concept or a case study with a vague description. Since they do not provide artifacts, the findings in the example applications are not reproducible and therefore questionable from a scientific point of view. Furthermore, there is no truly integrated approach yet. The reviewed approaches just reuse general-purpose process mining software (e.g., Disco, ProM, and Celonis platform). Below, the main research gaps of the reviewed approaches compared to traditional value stream mapping are discussed in more detail, along with possible solutions.

5.1 Aggregation level

Process mining operates at the instance/activity level. In contrast, value stream mapping operates at a more aggregated level. It consolidates subsequent activities on the same resources and groups products with production similarities into product families. Due to the intricate nature of production processes, an integrated approach should support both aggregation levels. The goal of combining value stream mapping and process mining in production is to provide a clear overview of the production process and offer details for in-depth analyses where needed.

5.2 Perspectives

In process mining, the choice of case identifier determines the perspective from which the process is viewed. For example, in the reviewed approaches, processes are described from the perspective of the item, order, or unit load. Although traditional value stream mapping primarily takes an item-related view [39], its map also integrates other relevant perspectives for production process improvement. For example, the information flow shows an order-related view, while the process key figures show a resource-related one. Recent object-centric process mining techniques may be possible solutions to close this gap.

5.3 End-to-end depiction

Process mining claims to analyze end-to-end processes. However, there is no support for decoupling points [40]. One example of decoupling is a Kanban regulation cycle with a supermarket store. The problem is the lack of a common identifier, which does not exist. The parts are produced or supplied according to consumption. They are interchangeable and cannot generally be traced back to individuals. One possible solution to this problem may be the quantity-related process mining approach proposed by Graves et al. [41].

5.4 Process model

The process models discovered in the reviewed approaches are usually represented as DFG, BPMN, or Petri net (cf. Table 3). Such notations have formal semantics that are necessary for the automated discovery of processes. In contrast, value stream mapping uses a largely standardized—though not formalized—set of symbols tailored to production optimization [1, 9]. The value stream map integrates all relevant information, including production planning and control logic, customer and supplier information, and key figures. However, it lacks the formal semantics necessary for automation. To close this open research challenge, future research should focus on formal semantics of value stream mapping elements. The ontologies by Knoll [28] and Horsthofer-Rauch et al. [34] are the first starting points. However, there are no direct connections to event data for relevant information systems, such as ERP and MES.

5.5 Future research directions

In order to close these research gaps and truly integrate both worlds, novel process mining techniques dedicated to value stream mapping are needed. Rather than simply reusing general-purpose process mining software, it is necessary to incorporate the semantics of production and value stream mapping. It is only then possible to depict an abstracted, end-to-end production process with all the relevant information for lean production improvements, as well as further details where needed. Future research should focus on the following directions:

1. multi-object event data with semantics (e.g., resources),
2. decoupling points (to enable a door-to-door process depiction within a production plant),
3. abstraction toward the value stream mapping level, and
4. formal semantics of value stream mapping elements directly connected to event data.

6 Conclusion

This systematic literature review article aimed to identify, compare, and synthesize existing approaches that combine value stream mapping and process mining in production. Following PRISMA 2020, a total of 21 out of the 2,682 initially identified records were included in the descriptive analysis and synthesis. The selection and data collection process was conducted by a single reviewer. To mitigate potential biases based on this limitation, an iteratively adapted protocol was used for guidance, and the results were discussed by all authors. With the first included records published in 2019, combining value stream mapping and process mining is a relatively new approach.

Nearly half of the affiliations are German universities and research institutes. Industry involvement is also notable, with approximately one quarter of affiliations coming from companies. This signals substantial industrial interest and application potential. While most reviewed approaches are conceptual/initial or only present partial aspects, three more advanced approaches were identified.

For practitioners, the reviewed approaches can offer first valuable benefits, particularly when used in conjunction with in-depth analyses and traditional value stream mapping. However, further research is needed to truly integrate both worlds. The review revealed research gaps related to aggregation level, perspectives, end-to-end depiction, and process modeling. To automatically discover end-to-end value stream maps with all relevant information integrated for lean production improvement, its semantics have to be formalized and used for an abstraction toward the value stream mapping mapping level. As a primary contribution of this review article, four research directions have been suggested to address these gaps. Overall, combining value stream mapping and process mining in production could revolutionize traditional value stream mapping.

Declarations

Authors contribution Tim Teriete conducted the review, analyzed the data, drafted the manuscript, and designed the figures. Klaus Erlach, Thomas Bauernhansl, and Wil van der Aalst provided the expert guidance. All authors discussed the results, commented on the manuscript, and approved the final version.

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