Journal of Engineering Managment and Soft Computing (JEMSC)

A Systematic Review of the Process Mining Literature in the Supply Chain

Mahdieh Arghiani[1], Jalal Rezaeenour[2]✉ Ali Rahnama[3] and Zahra Roozbahani[4]

1. PhD Student, Department of Industrial Engineering, Faculty of engineering, Qom University of Technology, Qom, Iran. arghiani.m@qut.ac.ir
2. Corresponding Author, Prof, Department of Industrial Engineering, University of Qom, Qom, Iran. j.rezaee@qom.ac.ir
3. PhD Student, Department of Industrial Engineering, Faculty of engineering, Qom University of Technology, Qom, Iran. . rahnama.a@qut.ac.ir
4. Assistance Prof, Department of computer Engineering, National University of Skill, Qom, Iran. zroozbahani@nus.ac.ir

Article Info

Article type:
Research Article

Article history:
Received 3 February 2026
Received in revised form
9 March 2026
Accepted 6 June 2026
Published online 1 July 2026

Keywords:
process mining, supply chain, data-to-value, production, logistics.

ABSTRACT

This paper presents a systematic and comprehensive review of PM applications across all critical SC domains. The study identifies key trends, leading countries—specifically highlighting Germany as the leading nation in this research field—widely adopted methods and tools, and the major challenges faced by practitioners. A five-layer analytical framework based on the "Data-to-Value" is introduced to classify PM challenges in SC contexts. The findings reveal a strong emphasis on production and logistics, with discovery as the most frequently applied PM method. Disco and ProM are identified as the most commonly used tools, while data quality and completeness, human factors and expertise, organization and stakeholders, integration of data sources, model complexity and scalability, and efficiency remain significant challenges. The study also highlights the growing importance of predictive analytics and the need for domain-specific adaptations of PM techniques. Ultimately, this review identifies research gaps and offers recommendations for advancing the integration of PM into SC, emphasizing the potential for future synergies between data-driven process analysis and SC optimization.

Cite this article: Arghiani, M. & et al, (2026)., A Systematic Review of the Process Mining Literature in the Supply Chain. *Journal of Engineering Management and Soft Computing,* 12 (3). 111-149.

DOI: https://doi.org/10.22091/jemsc.2026.15287.1347

DOI: https://doi.org/10.22091/jemsc.2026.15287.1347

Publisher: University of Qom

1) Introduction

The Supply Chains (SC), as a complex system of processes, communication, and cooperation among members, plays a critical role in the provision of goods and services. A direct relationship exists between market competition, complex changes in supply and demand, and SC performance. In this context, Process Mining (PM) has gained significant momentum among researchers as a powerful mechanism for data analysis and identifying hidden patterns. By applying PM to SC data, patterns that improve performance can be discovered, including those related to supply and demand, production planning, inventory control, marketing, and distribution. Furthermore, PM can contribute to identifying risks and problems within the chain, enabling the detection of error factors and risk potentials so that appropriate preventive measures can be implemented. However, despite its potential, the application of PM is not without challenges.

In recent years, PM research has increasingly moved beyond isolated and exploratory use cases toward large-scale and strategic SC applications. In particular, it has been demonstrated that while PM has reached a level of maturity enabling its application in tactical and strategic SC decision-making—including network-level coordination and cross-organizational process alignment—its implementation continues to face substantial challenges. These include poor data quality, difficulties in systems integration, and limitations in tracking materials within process industries. Furthermore, cross-organizational data sharing remains critically hindered by privacy concerns and a lack of standardization (Oldenburg et al., 2025). Moreover, recent literature emphasizes the role of PM in addressing emerging SC challenges such as sustainability, circular economy, and resilience. It has been shown that process-mining-driven digital transformation enables enterprises to monitor material flows, reduce waste, and improve circular SC performance by providing end-to-end transparency of logistics processes (Mukha, 2025). These developments indicate a clear shift from efficiency-oriented applications toward sustainability-driven and value-oriented process improvement. A Systematic Literature Review (SLR) aimed to develop a model for measuring the performance of custom production processes by employing a PM approach. This study identifies critical challenges, including the emergence of highly complex "spaghetti" process models, increased uncertainty in order lead times, and rising operational costs within the SC. Furthermore, the research underscores the difficulties in reconfiguring SC networks and the necessity of normalizing diverse performance indicators to achieve accurate measurement in customized production environments (Wikusna et al., 2024). The researchers reviewed the application of PM in manufacturing, categorizing existing research into six key areas and identifying critical challenges related to information technology (IT) and governance that hinder its adoption in complex industrial environments (Oliveira et al., 2025). A decentralized edge–cloud PM approach has been introduced that enables the analysis of distributed processes close to data sources (Reiter et al., 2025). Such architectures are especially suitable for modern SCs operating in Industry 4.0 and Industry 5.0 environments, where real-time data from sensors, IoT devices, and cyber–physical systems must be analyzed with low latency and high scalability. Finally, knowledge and expertise gaps in PM initiatives have been highlighted, arguing that effective application requires interdisciplinary collaboration between domain experts, process analysts, and data scientists (Pradhan et al., 2025). In SC settings, this challenge is amplified due to the complexity of logistics networks and the diversity of stakeholders involved.

Existing literature often focuses on isolated segments of the SC, such as logistics or production, and prior reviews have primarily concentrated on application areas, specific logistics sub-domains, or the maturity of cross-organizational applications. Specifically, no study has yet provided a consolidated classification that reveals the prevalence and distribution of different PM techniques, including discovery, conformance, and enhancement. Furthermore, while numerous algorithms have been proposed or applied, the literature lacks a thematic categorization to understand the frequency and context of use for various PM algorithms versus hybrid algorithmic frameworks. Finally, the tools employed to conduct this research—ranging from academic platforms to commercial software—remain underexplored in terms of their adoption patterns across the field.

Based on selected articles from scientific journals and conferences, this study analyzes the main findings, key trends, leading countries, widely adopted methods and tools, and the critical challenges faced by practitioners. The primary objectives are to collect, analyze, and integrate the existing literature to delineate the current state of PM application, identify its main thematic groups, and highlight promising areas for future use. Ultimately, this review seeks to identify research gaps and potential synergies between PM and SC, while also offering recommendations to address the identified challenges.

This study makes a distinctive contribution to the literature by providing a comprehensive examination of PM applications across the entire SC landscape. Moving beyond previous reviews that focused on isolated operational areas, this research investigates PM's impact across all critical domains: from upstream activities, including supplier selection and procurement, to core operations such as production planning and manufacturing; from tactical functions like inventory control to downstream processes encompassing distribution and logistics. Crucially, it bridges the gap between operational SC management and strategic business functions by incorporating demand forecasting, sales, marketing, and research and development (R&D).

To ensure both qualitative rigor and quantitative impact assessment, this review systematically identifies and classifies the highest-quality articles in this domain through the integrated application of Kitchenham's systematic review protocol and the Ordinatio 2.0 method. The innovation of this research is further underscored by its introduction of a five-layer analytical framework based on the "Data-to-Value Pipeline" for the systematic classification of PM challenges in the SC. By considering the multi-layered and inter-organizational nature of the SC, this framework categorizes challenges. In doing so, it not only identifies the main categories of challenges but also provides a roadmap for future research, enabling a comprehensive analysis of research gaps.

The remainder of the paper is structured as follows. Section 2 introduces the definitions and theoretical foundations relevant to PM and SC. Section 3 outlines the methodology employed in this review, while Section 4 presents a five-tier conceptual framework for analyzing PM challenges in SCs. Section 5 presents the results. Section 6 discusses the findings in the context of current PM practices and suggests directions to address the identified challenges. Section 7 highlights the research gaps, and Section 8 concludes the paper and outlines future research directions.

2) Definitions and Theoretical Foundations

This section provides the definitions and theoretical foundations underlying the present study, beginning with the core concepts of PM and SC, and culminating in the theoretical basis for the proposed five-layer analytical framework.

2-1) Process Mining (PM)

PM is a research method that reconstructs, analyzes, and optimizes business processes by examining event logs recorded in information systems (van den Elzen et al., 2025; Yari Eili et al., 2023). In complex operational environments, such as SCs and industrial systems, PM has been applied to support decision-making, predictive monitoring, and compliance analysis across interconnected processes (Oldenburg et al., 2025; W. M. P. van der Aalst et al., 2024). PM addresses three fundamental perspectives: the process perspective (how?), the organizational perspective (who?), and the case perspective (what?) (Thiede et al., 2018). These perspectives are particularly relevant in inter-organizational settings, where multiple stakeholders, systems, and objects interact within a single process execution (Goossens et al., 2024; Yang et al., 2024).

The methodology is built upon three core pillars: discovery, conformance checking, and enhancement (W. van der Aalst, 2016; Wangelik et al., 2025). The applicability of these pillars has recently been extended to support sustainability-oriented and circular process optimization by enabling end-to-end transparency of material and information flows (Mukha, 2025).

The first and most important stage of PM is discovery, which involves understanding the structure of the process (Chiò et al., 2021). In this stage, the objective is to discover a process model that describes the underlying process from the event logs (Kedem-Yemini, 2020; G. Park et al., 2024). To address the limitations of classical workflow-based discovery in multi-entity processes, advanced modeling techniques such as object-centric and multi-dimensional PM have been proposed (Goossens et al., 2024; Khayatbashi et al., 2024). In this stage, an event log is fed into a process discovery algorithm, which produces a visualized process model as output (Eulerich et al., 2025). These models depict the control flow between activities using standardized symbols (Yari Eili et al., 2022) and are increasingly utilized as analytical artifacts for operational monitoring and managerial decision support in large-scale industrial and SC contexts (Monti et al., 2024; Oldenburg et al., 2025).

The second pillar, conformance checking, serves as a form of validation in relation to process discovery. It examines whether the reality, as recorded in the event logs, conforms to a reference process model (Chiò et al., 2021; van den Elzen et al., 2025). This capability is essential in distributed and cross-organizational processes, where deviations may emerge across organizational boundaries and heterogeneous information systems (Yang et al., 2024). By comparing the model to the log and vice versa, this approach identifies deficiencies and contradictions, enabling a more accurate reflection of reality (Gianola et al., 2025; Grohs et al., 2025; Rafiei et al., 2025; Yari Eili et al., 2021). To support timely analysis in data-intensive environments, modern architectural solutions such as decentralized and edge–cloud-based PM have been introduced (Reiter et al., 2025).

The third pillar, enhancement, aims to extend or improve an existing process model by leveraging real information recorded in event logs (Bakhshi et al., 2023). The success of such enhancement initiatives often depends on organizational factors, including governance mechanisms, analytical expertise, and collaboration between business and IT stakeholders, particularly in complex SC settings (Mamudu et al., 2025; Pradhan et al., 2025).

2-1-1) Some of the PM Algorithms

Genetic miner (GM) is an algorithm that obtains the optimal process model by repeatedly selecting individuals and reproducing them through mutation across different generations. This algorithm is termed an evolutionary process, as it continuously and iteratively searches by combining and mutating individuals within the population. The steps of this algorithm are: (1) population initialization (dataset creation), (2) fitness-based selection (optimal individual identification), (3) reproduction (crossover and mutation operations), and (4) convergence termination (fitness threshold achievement) (Dzihni et al., 2019).

Alpha miner (AM) is an algorithm applied to form simple process models by analyzing event logs (J. Park et al., 2020). This algorithm constructs a Petri net model from event logs (Rabbi et al., 2024). The sensitivity to incomplete logs constitutes the main weakness of AM. It is recommended to use complete and noise-free event logs to improve the performance of AM (Chamorro et al., 2013).

Fuzzy miner (FM) is an algorithm that analyzes and evaluates process patterns through "significance" and "correlation" criteria (Gurgen Erdogan et al., 2018). The significance metric evaluates event precedence by frequency, weighting more frequent precedence relationships as more significant. The correlation metric evaluates the strength of relationships between events, calculated through either shared data attributes or activity name similarities (Jans et al., 2011; Pan et al., 2021).

Heuristic miner (HM) is an algorithm through which complex processes are predicted by analyzing frequency, cause-and-effect relations, and data clustering to identify the optimal process model. The process decomposes the event log analysis into three phases: (1) extracting dependency graphs, (2) combining discovered relations, and (3) analyzing far-reaching dependency interactions (Rabbi et al., 2024).

Inductive miner (IM) is a data-driven process discovery algorithm that applies machine learning methods to extract the structure of process workflows from event logs (Rabbi et al., 2024). This approach constructs a directly-follows graph (DFG) from the event log, then applies graph analysis through cut detection to reveal process relationships (Bakhshi et al., 2023).

Some other algorithms used in the selected articles are described as follows.

Multidimensional Conformance Classification Algorithm: This algorithm is a method that automatically assigns the most suitable reference process model to each individual part by comparing its event log against multiple predefined models. It evaluates three key conformance metrics for each comparison: fitness (how well the log matches the model), precision (whether the model avoids underfitting), and generalization (the model's ability to handle unseen behavior). Based on these metrics, the algorithm selects the optimal process model for each part, enabling detailed deviation analysis. This approach allows practitioners to identify which parts follow standardized processes and which exhibit wasteful variations. The algorithm was successfully validated in an automotive logistics case study involving over 7,500 parts and 15 reference processes (Knoll et al., 2019).

Cut Transform (CT): This algorithm provides a structured approach to identifying relationships between process paths and performance indicators in production systems. By separating each sequence of operations into two distinct segments at various cut points, this method enables comparison between expected and observed attribute behaviors. The transformation removes the temporal order from data, creating a structured dataset suitable for conventional data mining techniques such as association rule discovery to detect hidden dependencies (Choueiri et al., 2021a).

Iterative PM (i-PM): An i-PM algorithm has been proposed that integrates fuzzy set theory with association rule mining to discover hidden relationships between process parameters and customer satisfaction levels in SC networks. The algorithm converts quantitative process data into fuzzy sets, applies multiple minimum support thresholds for different parameters, and iteratively identifies significant association rules that can help organizations optimize their processes and enhance customer satisfaction (Lau, Ho, Zhao, et al., 2009).

Transition System Generation Algorithm: A transition system generation algorithm has been proposed that constructs a product-oriented transition system from event logs by replaying traces and applying state and event representation functions. This algorithm serves as the foundation for remaining time prediction in manufacturing systems by annotating states with historical completion time information (Choueiri et al., 2020).

2-2) Supply Chain (SC)

Today, the SC, as a complex and interconnected system, faces growing challenges—from globalization to evolving customer demands, rapid innovation, and mounting uncertainties (Ghag et al., 2025). Therefore, multiple failure risks can arise at various stages of the process, all of which hinder its efficiency and performance (Shiying Ni et al., 2022).

The roots of SC management (SCM) trace back to Michael Porter's "value chain" concept. In 1982, Keith R. Oliver and Michael D. Webber first introduced the term "SCM" in Outlook magazine, formally defining the field (Hou et al., 2015). SC management (SCM) refers to the coordination of all activities needed to satisfy customer requirements (Anich et al., 2024). It supervises business activities and the correspondence among suppliers, customers, and other members within the chain, and maintains the coordination and integration of key business processes through key suppliers. These suppliers provide products, services, and information that generate added value for customers and other beneficiaries, thereby covering the entire value chain. According to Lambert and colleagues, SCM—as a multifaceted and integrated framework—encompasses eight critical sub-processes: (1) product development and commercialization, (2) demand management, (3) supplier relationship management, (4) customer relationship management, (5) order fulfillment, (6) production flow management, (7) customer service management, and (8) returns management (Hou et al., 2017). SCM also handles the synchronization of manufacturing processes, logistics activities, and material management across the organization (Q. Wang et al., 2024). In terms of service level, it is crucial to understand that what benefits one party—whether a provider or a customer—may not necessarily benefit the other (Aghazadeh et al., 2025).

Given this high degree of interdependence among SC activities, effective management requires a comprehensive understanding of how processes are executed across organizational functions and partners. Approaches that enable the analysis of end-to-end process behavior and the coordination of interconnected workflows support improved transparency, alignment, and control across SC operations, particularly in complex and multi-actor environments (Oldenburg et al., 2025; W. M. P. van der Aalst et al., 2024). Moreover, achieving such integration depends not only on technical solutions but also on organizational capabilities that facilitate collaboration, governance, and consistent process execution across the SC (Mamudu et al., 2025).

3) Methodology

This section describes the systematic review methodology adopted in this study. The initial and most fundamental step in a systematic review is the formulation of precise and relevant research questions. These questions establish the foundation of the study and direct the subsequent data extraction process. A critical aspect of this stage involves ensuring that the questions are specifically designed to address the identified research gap and to provide answers that contribute to filling this void in the existing literature. Accordingly, this study is guided by the following research questions:

RQ1: What are the prevailing trends and statistical distributions evident in past studies concerning the application of PM methods in SC?

RQ2: Which countries are identified as leading contributors in the research domain of PM within the SC context?

RQ3: Which specific fields in the SC have demonstrated the highest adoption of PM methods?

RQ4: What are the most frequently adopted PM methods and applied tools in the available body of literature?

RQ5: What are the most critical challenges and barriers identified across the reviewed studies?

RQ6: What solutions are proposed to overcome the identified challenges?

This study is applied research in terms of its purpose and adopts a qualitative approach based on the SLR method. A systematic review is a structured process that involves conducting a systematic search to evaluate and synthesize research findings (Grant et al., 2009). This methodology comprises three main phases: (1) planning, (2) execution, and (3) reporting (Maita et al., 2018).

To ensure rigor, this research employs an integrated approach combining the systematic review model proposed by Kitchenham et al. (2009) with the Ordinatio 2.0 method (Pagani et al., 2023). The detailed workflow of the review process is illustrated in Figure 1.

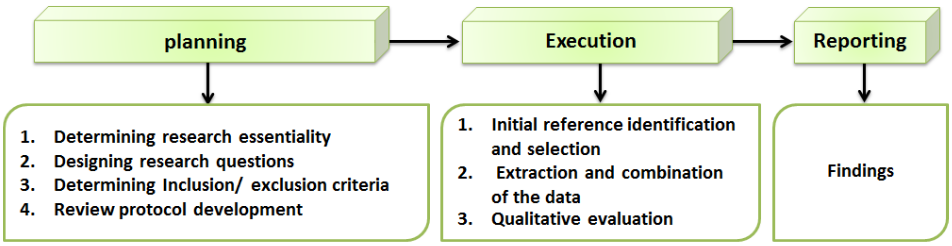

Figure 1. Systematic Review Process

The Ordinatio 2.0 method, calculated using Equation 1 (Pagani et al., 2023), offers a quantitative measure to supplement the qualitative evaluation, thereby enhancing the objectivity and reproducibility of the review. While other systematic review methods offer general checklists or focus on specific synthesis aspects, Kitchenham, augmented by the Ordinatio 2.0 index, provides a more comprehensive and numerically supported framework for navigating the complexities of empirical evidence.

$$\text{InOrdinatio } 2.0 = \left\{[\Delta^*(IF)] - \left[\lambda^*\left(\frac{\text{ResearchYear} - \text{PubYear}}{\text{CitedHalfLife}}\right)\right] + \Omega^*\left[\frac{Ci}{(\text{ReseachYear} + 1) - \text{PubYear}}\right]\right\} \quad (1)$$

Δ: Importance of journal metrics (between 0 and 10)

IF: Impact Factor

λ: Importance of the article's novelty (publication year) (between 0 and 10)

Ω: Importance of the article's average annual citations (between 0 and 10)

Ci: Number of Citations

This integration aims to quantify qualitative judgments and increase objectivity in the selection of final articles. The main advantages of this combined approach are as follows:

• Objectification of Qualitative Evaluation: By employing the Ordinatio 2.0 formula—which combines the number of citations, year of publication, and impact factor—subjective and biased judgments in the qualitative evaluation stage are minimized, and a transparent, data-driven process is established.

• Intelligent Prioritization of Articles: This method enables the ranking of articles based on their scientific impact. Consequently, in-depth and detailed study is prioritized for articles with higher credibility, while time spent on less impactful articles is minimized.

• Increased Precision in Final Screening: Combining traditional inclusion/exclusion criteria with the quantitative InOrdinatio index creates a robust second filter. This leads to the selection of a set of articles with the highest methodological quality and greatest scientific impact for the synthesis and final analysis stage.

• Enhanced Transparency and Replicability: The use of a clear numerical index alongside qualitative assessments facilitates the documentation of the article selection process and significantly enhances the replicability of this systematic review.

3-1)The Search Process

The keywords presented here were derived based on term frequency within the existing literature on SC elements (process mining, supply chain, logistics, inventory control, demand forecasting, supplier selection, inventory management, production planning, research and development, marketing, sales, inventory processes, production, distribution, and purchase) (Table 1).

The search strategy employed five prominent and well-regarded databases—Web of Science, Scopus, Google Scholar, Science Direct, and Emerald—to capture the extant literature. The multidisciplinary breadth of Web of Science, Scopus, and Google Scholar was combined with the subject-specific depth of Science Direct and Emerald. This integrated approach ensures both breadth and depth in the literature search, thereby maximizing the likelihood of identifying all relevant studies and minimizing the risk of publication bias in this systematic review.

Due to the limitation of Science Direct regarding the number of Boolean operators (max 8 per field), the keywords were searched in two distinct groups in combination with "supply chain." Subsequently, duplicate articles were removed. For Emerald, where constructing a complex query in a single line is challenging due to its search interface being based on multiple separate boxes, each keyword was searched in combination with "supply chain" across the title, abstract, and keyword fields. Duplicate articles were then removed from the Emerald search results as well. For the other databases, predefined advanced search filters were applied through the available menus to refine the results based on criteria such as publication date and language. A total of 1,521 articles were retrieved through a search of title, abstract, or keywords in the databases up to the end of 2025 (Table 1).

Table 1. Search Strategies

Rows	Digital Library	Strategy	Search Results
1	Web of Science	Queries: TS=(("supply chain" OR "Logistics" OR "Inventory control" OR "Demand forecasting" OR "Supplier selection" OR "Inventory management" OR "Production planning" OR "Research and development" OR "Marketing" OR "Sale" OR "inventory processes" OR "Production" OR "Distribution" OR "Buy") AND "Process mining") AND PY=(1800-2025) AND LA=(English) and Proceeding Paper or Article (Document Types)	446
2	Scopus	Queries: TITLE-ABS-KEY (("process mining") AND ("supply chain" OR "Logistics" OR "Inventory control" OR "Demand forecasting" OR "Supplier selection" OR "Inventory management" OR "Production planning" OR "Research and development" OR "Marketing" OR "Sale" OR "inventory processes" OR "Production" OR "Distribution" OR "Buy")) AND P UBYEAR > 1990 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English"))	763
3	Google Scholar	Queries: allintitle: ("supply chain" OR Logistics OR "Inventory control" OR "Demand forecasting" OR "Supplier selection" OR "Inventory management" OR "Production planning" OR "Research and development" OR Marketing OR Sale OR "inventory processes" OR Production OR Distribution OR Buy) "Process mining"	157
4	Science Direct	Queries: Title, abstract, keywords: "process mining" AND ("supply chain" OR Logistics OR "Inventory control" OR "Demand forecasting" OR "Supplier selection" OR "Inventory management" OR "Production planning") Title, abstract, keywords: "process mining" AND ("Research and development" OR Marketing OR Sale OR "inventory processes" OR Production OR Distribution OR Buy)	133
5	Emerald	"supply chain" AND "Process mining" "Logistics" AND "Process mining" "Inventory control" AND "Process mining" "Demand forecasting" AND "Process mining" "Supplier selection" AND "Process mining" "Inventory management" AND "Process mining" "Production planning" AND "Process mining" "Research and development" AND "Process mining" "Marketing" AND "Process mining" "Sale" AND "Process mining" "inventory processes" AND "Process mining" "Production" AND "Process mining" "Distribution" AND "Process mining" "Buy" AND "Process mining"	22
Total			1521

As illustrated in Figure 2, the highest frequency of published articles (106 articles) is related to the year 2024, as recorded in the Scopus database.

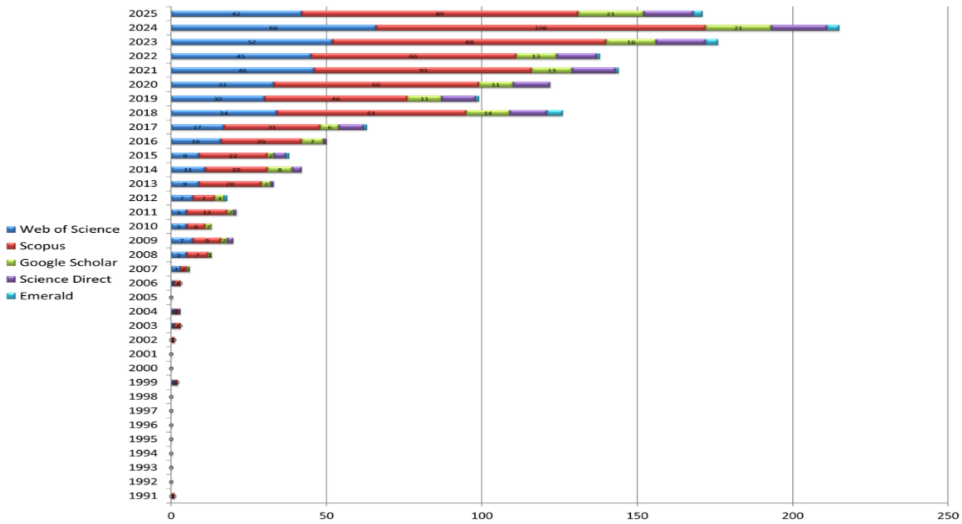

Figure 2. Frequency of Articles Published Up to the End of 2025

The articles were reviewed and screened based on predefined inclusion and exclusion criteria, as outlined below.

Inclusion criteria:

Articles containing the specified keywords in the title, abstract, or keyword fields

Articles available online

Articles published without time restriction up to the end of 2025

Articles published in journals, magazines, or presented at conferences

Exclusion criteria:

No electronic access

Non-English articles

Review articles, books, and book chapters

Single-page writings, posters, or executive briefings

Articles where PM and SC are not the core focus

Duplicate articles

The screening process began with an assessment of the article titles, followed by the abstracts and keywords. Only the articles that met all the criteria at this stage were transferred to the next phase. In cases where insufficient information was available to determine whether an article should be included or excluded, the article was moved to the subsequent step. The screening procedure consisted of six distinct stages:

First screening: Duplicate items were identified and removed using EndNote software.

Second screening: Accessible articles from journals, magazines, and conferences were selected. During this stage, duplicate or irrelevant studies, as well as those not meeting the inclusion and exclusion criteria, were removed.

Third screening: The titles, abstracts, and keywords were checked for an exact match with the search terms. Duplicate articles and those with multiple similar versions were also excluded at this point.

Fourth screening: The abstracts and keywords of the remaining articles were examined for consistency with the research objectives.

Fifth screening: A screening was performed based on the InOrdinatio 2.0 method. Considering the interdisciplinary nature of the PM field in the SC and the rapid pace of technological developments in this area, the Method Ordinatio 2.0 was applied with weights of Δ=10, λ=10, and Ω=5. For articles without any citation metrics, a Δ weight of zero was assigned. This approach enabled the inclusion of foundational and highly-cited works while also prioritizing recent articles reflecting the latest technological advancements.

Sixth screening: A full-text review was conducted to determine the extent to which the selected articles focused on applying PM in different SC fields. This ensured that the SC was the main scope of the research and not merely the context of a case study.

3-2) Quality Assessment and Validation

In the fifth phase of the selection process, a rigorous quality assessment was conducted on the 257 articles retained from the previous stage. The evaluation was performed using the criteria established by the Kitchenham protocol, with each study being appraised for its relevance and suitability in addressing the research questions. Based on this assessment, the articles were subsequently ranked in descending order according to their Ordinatio 2.0 scores (Figure 3).

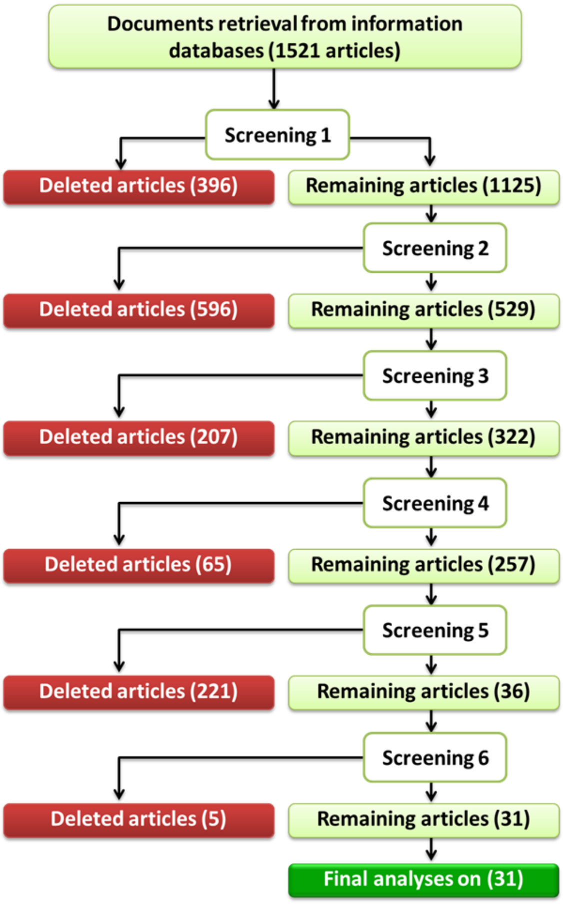

Figure 3. The Process of Review and Selection of Articles in the Systematic Review of Research

To select the highest-quality articles, an initial threshold was established based on the main breaking point (Rank 20, corresponding to an Ordinatio 2.0 score of 131.18). To ensure a comprehensive review of the literature, the final inclusion criterion for the fifth screening phase was subsequently set at a more inclusive threshold of an Ordinatio 2.0 score greater than 70 (Rank 36, Figure 4).

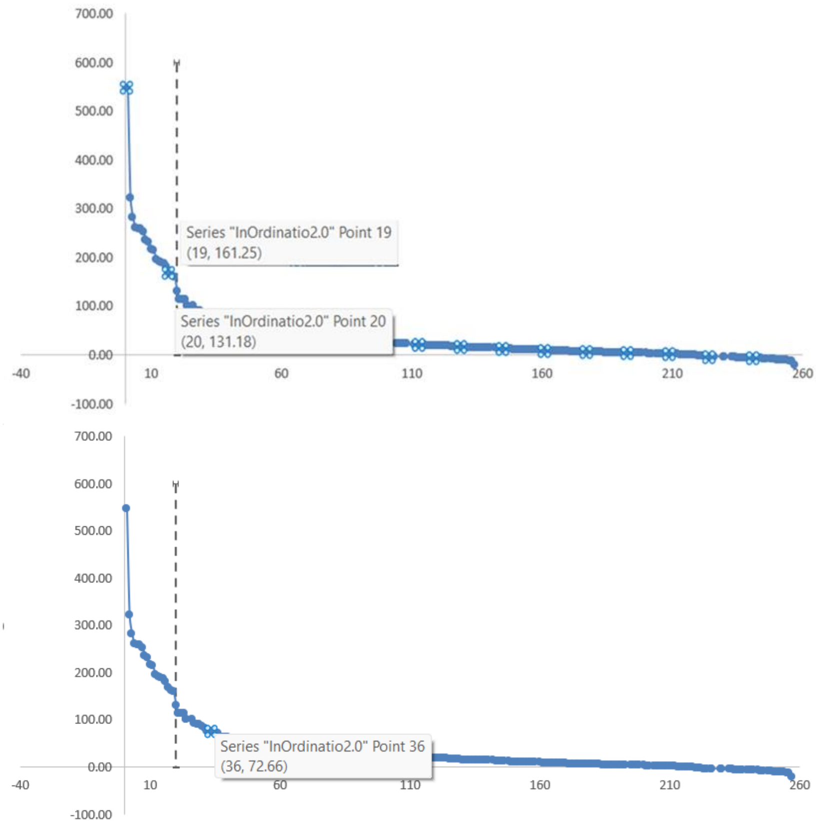

Figure 4. Ranking of Articles in the Fifth Screening and Determination of the Cut-Off Rank for Passing This Stage

Following this screening, the top 36 articles were selected for full-text review. A more detailed assessment of these articles led to the exclusion of irrelevant studies, resulting in a final set of 31 articles.

Table 2. The Details of the Selected Articles

Rows	Rank	Reference	Publication	Publish year	Citation count	Impact factor	InOrdinatio 2.0	Reference count
1	1	(Aloini et al., 2020)	International Journal of Information Management	2020	40	52.70	547.68	68
2	2	(Choueiri et al., 2020)	Journal of Manufacturing Systems	2020	86	26.90	322.53	55
3	3	(Choueiri et al., 2021a)	Journal of Manufacturing Systems	2021	24	26.90	282.42	38
4	4	(Knoll et al., 2019)	Expert Systems with Applications	2019	170	16.40	261.04	49
5	5	(Lorenz et al., 2021)	International Journal of Production Research	2021	108	17.70	260.42	46
6	6	(Lugaresi et al., 2023)	Computers in Industry	2023	34	22.00	258.55	42
7	7	(Sánchez et al., 2020)	Computers in Industry	2020	58	22.00	253.53	81

Rows	Rank	Reference	Publication	Publish year	Citation count	Impact factor	InOrdinatio 2.0	Reference count
8	8	(W. M. P. van der Aalst et al., 2024)	Computers in Industry	2024	12	22.00	237.37	25
9	9	(Er et al., 2018)	Journal of Enterprise Information Management	2018	92	19.10	231.58	56
10	10	(May et al., 2024)	International Journal of Production Research	2024	26	17.70	217.70	64
11	11	(J. Park et al., 2014)	International Journal of Production Economics	2014	105	19.10	215.60	17
12	12	(Bodendorf et al., 2023)	Industrial Marketing Management	2023	37	15.40	196.30	62
13	13	(Lau, Ho, Zhao, et al., 2009)	International Journal of Production Economics	2009	87	19.10	192.80	24
14	14	(Choueiri et al., 2021b)	Journal of Intelligent Manufacturing	2021	20	18.00	190.09	48
15	15	(Y. Wang et al., 2014)	Expert Systems with Applications	2014	101	16.40	187.06	57
16	16	(C. K. H. Lee et al., 2016)	Expert Systems with Applications	2016	70	16.40	182.66	44
17	17	(S. k. Lee et al., 2013)	Expert Systems with Applications	2013	62	16.40	169.04	23
18	18	(Lau, Ho, Chu, et al., 2009)	Expert Systems with Applications	2009	73	16.40	161.91	16
19	19	(Ruschel et al., 2021)	Computers & Industrial Engineering	2021	43	13.20	161.25	55
20	20	(Loacker et al., 2025)	International Journal of Productivity and Performance Management	2025	5	12.00	131.18	49
21	21	(Monti et al., 2024)	Software and Systems Modeling	2024	24	7.80	115.37	65
22	22	(Ramires et al., 2022)	International Journal of Lean Six Sigma	2022	29	9.10	114.74	51
23	23	(Rudnitckaia et al., 2022)	IEEE Access	2022	34	8.50	113.74	29
24	24	(Khakpour et al., 2025b)	International Journal of Lean Six Sigma	2025	5	9.10	102.18	50
25	24	(Khakpour et al., 2025a)	International Journal of Lean Six Sigma	2025	5	9.10	102.18	61
26	25	(Zerbino et al., 2019)	Sustainability	2019	39	8.70	102.16	59
27	26	(Celik et al., 2025)	IEEE Access	2025	4	8.50	93.68	58
28	27	(Tridalestari et al., 2023)	IEEE Access	2023	9	8.50	92.30	49
29	28	(Tran et al., 2021)	Applied Sciences	2021	46	5.90	90.75	86
30	29	(Kermani et al., 2024)	IEEE Access	2024	3	8.50	87.37	42

Rows	Rank	Reference	Publication	Publish year	Citation count	Impact factor	InOrdinatio 2.0	Reference count
31	30	(Novák et al., 2022)	Processes	2022	33	5.60	83.74	64
			Average		47.87	15.97	185.77	49.45

The characteristics of these 31 articles are summarized in Table 2. The mean citation count for the included articles was 47.87, the mean impact factor was 15.97, the mean InOrdinatio 2.0 score was 185.77, and the mean reference count was 49.45.

4) A Proposed Five-Tier Conceptual Framework for Analyzing PM Challenges in SCs

To conduct a structured analysis and synthesis of the fragmented literature on PM in SCs, a novel five-tier analytical framework is proposed. This framework is conceived as a Data-to-Value Pipeline, organizing the multifaceted challenges reported in the literature according to their locus in the sequential progression from raw data to ultimate business value. The Data-to-Value model offers a structured process for managing large-scale data projects (Leidner, 2022), rendering it particularly suited to the data-intensive and multi-layered context of modern SCs. The tiered structure is deliberately designed to reflect the layered, multi-echelon nature of SCs and the interdisciplinary scope of PM research, encompassing both technical and organizational dimensions. The framework comprises the following five layers (Figure 5):

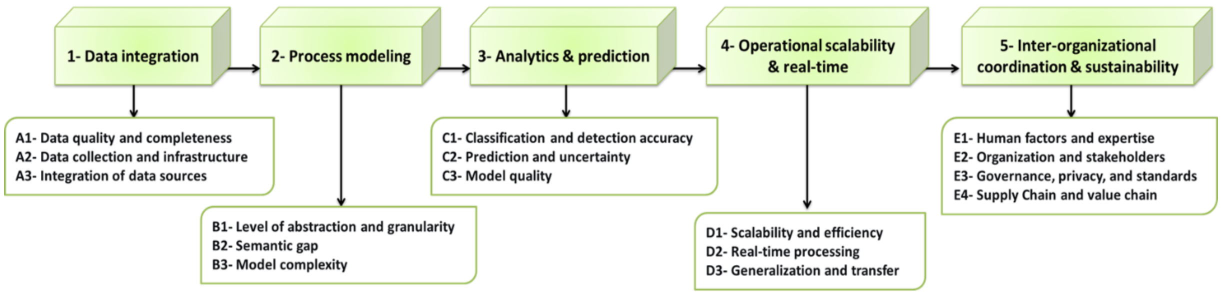

Figure 5. A Proposed Five-Tier Data-to-Value Pipeline Framework for PM Challenges in SCs

The framework consists of five distinct yet interconnected layers:

1. SC data integration layer: This layer encapsulates the challenges inherent in the foundational stages of data acquisition and preparation, including issues of data quality, completeness, and heterogeneity, as well as the technical complexities of integrating data from disparate sources such as Enterprise Resource Planning (ERP) systems, Warehouse Management Systems (WMS), Transportation Management Systems (TMS), IoT sensors, and Radio-Frequency Identification (RFID). As highlighted by recent case studies on complex processes like Purchase-to-Pay (P2P), extracting meaningful event data from systems such as SAP ERP is particularly challenging due to data scattered across numerous tables and weak relational schemas (Berti et al., 2025).

Table 3. Layer 1- Focus, Data Sources, and Key Challenges

Data source	Data type	Key challenge
ERP	Orders, invoices	Cross-organizational integration
IoT sensors	Location, temperature, humidity	High volume, real-time processing
RFID	Goods tracking	Reading accuracy, standards
WMS	Warehousing operations	Alignment with physical inventory
TMS	Transportation	Scheduling, delays

The sub-layers of layer 1 are as follows:

A1- Data quality and completeness

A2- Data collection and infrastructure

A3- Integration of data sources

2. SC process modeling layer: This layer addresses challenges in representing SC operations. It focuses on the difficulties in creating accurate and semantically meaningful models that capture the triple flow of materials, information, and finances. Key issues include abstraction granularity, the semantic gap between low-level event logs and high-level process models (Knoll et al., 2019), and the complexity of modeling object-centric interactions. Recent research has demonstrated that traditional PM techniques often result in overly complex, "spaghetti-like" process models when applied to interconnected processes (Wikusna et al., 2024), largely due to the convergence and divergence issues that arise from many-to-many relationships between business objects. To address these challenges, object-centric PM has emerged as a promising paradigm that captures the intricate relationships among multiple data objects, such as purchase orders, invoices, and payments, thereby providing a more accurate representation of real-world SC interactions (Berti et al., 2025).

Table 4. Layer 2- Flows, Examples, and Modeling Challenges

Flow Type	Example	Modeling Challenge
Material flow	From supplier to customer	Tracking across organizational boundaries
Information flow	Order, forecast, confirmation	Transmission delay, accuracy
Financial flow	Payment, credit, invoice	Temporal alignment with physical flow

The sub-layers of layer 2 are as follows:

B1- Level of abstraction and granularity

B2- Semantic gap

B3- Model complexity

3. SC analytics and prediction layer: This layer encompasses challenges inherent in extracting insights and foresight from process models and event data. It covers the accuracy of deviation classification, the reliability of predictive models under uncertainty (e.g., demand forecasting, lead time prediction), and the overall validity and robustness of analytical results. A critical aspect of ensuring this validity is the identification of concept drift, referring to the situation where a business process changes during the analysis period (Prathama et al., 2019). Detecting such drift—whether sudden, gradual, or recurring—is essential because evolving processes can render static models obsolete and undermine the reliability of any derived insights or predictions.

Table 5. Layer 3- Analytical Areas, Applications, and Key Challenges

Analytical Area	Application	Key Challenge
Demand forecasting	Production planning	Uncertainty, fluctuations
Lead time prediction	Inventory management	Customs delays, transportation disruptions
Anomaly detection	Fraud detection, Error identification	Sparse data
Risk analysis	Identifying vulnerability points	Complex dependencies

The sub-layers of layer 3 are as follows:

C1- Classification and detection accuracy

C2- Prediction and uncertainty

C3- Model quality

4. Operational scalability and real-time layer: This layer addresses the critical challenges of deploying PM solutions in real-world, large-scale SC environments. It encompasses issues of computational complexity and algorithmic scalability when handling "big data," the demands of real-time streaming analytics and dynamic updating, and the generalizability of solutions across different geographical scales and production contexts. It is emphasized that the majority of logistics activities typically occur without direct human supervision, a reality that underscores the necessity of data-driven methodologies (Knoll et al., 2019). PM is particularly relevant in this context, as it enhances process visibility and enables the continuous monitoring, assessment, and identification of waste at the level of individual parts and processes.

Table 6. Layer 4- Dimensions, Description, and Specific SC Challenges

Dimension	Description	Specific SC Challenge
Geographical scale	Global SC	Differences in language, regulations, culture
Volume scale	Millions of daily events	Distributed processing
Real-time capability	Real-time shipment tracking	Reporting delays
Flexibility	Supplier switching, route changes	Environmental dynamics

The sub-layers of layer 4 are as follows:

D1- Scalability and efficiency

D2- Real-time processing

D3- Generalization and transfer

5. Inter-organizational coordination and sustainability layer: This topmost layer captures the challenges that transcend the purely technical, focusing on the human, organizational, and societal context. It includes issues of divergent stakeholder objectives, cross-organizational data sharing and governance, data privacy and security, the need for explainability and human-in-the-loop validation, and the integration of broader sustainability criteria (environmental and social) into process analysis.

Table 7. Layer 5- Concepts, Examples, and Key Challenges

Concept	Example	Key Challenge
Inter-organizational trust	Data sharing	Privacy, competition
Governance	Reporting standards	Divergent national regulations
Environmental sustainability	Carbon footprint tracking	Accurate measurement
Social sustainability	Supplier working conditions	Transparency in lower-tier suppliers

The sub-layers of layer 5 are as follows:

E1- Human factors and expertise

E2- Organization and stakeholders

E3- Governance, privacy, and standards

E4- SC and value chain

This five-layer framework serves as the analytical lens for the systematic review, allowing for the categorization of the literature and the identification of critical gaps, particularly at the interfaces between technical implementation and organizational reality in SCs.

5) Results

This section reports the key findings derived from the systematic analysis of the selected articles, highlighting the main trends, applications, and challenges of PM in the SC.

5-1) Analysis of Metadata

This subsection analyzes the metadata of the selected articles to identify key bibliometric patterns, including publication year, geographical distribution, and leading journals and conferences in the field.

The temporal distribution of the reviewed articles is illustrated in Figure 6. As depicted, the volume of publications has increased from 2019 onwards.

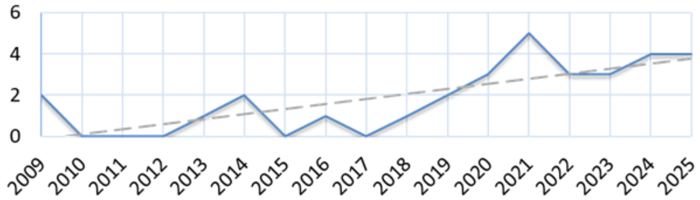

Figure 6. Frequency of Publication of Selected Articles in Different Years

The distribution of the reviewed articles by source type is presented in Figure 7. As illustrated, all of the articles included in this review are journal publications.

Figure 7. Percentage Distribution of Selected Articles in Journals and Conferences

The distribution of the selected articles across various publication outlets is presented in Figure 8. The highest number of articles were published in Expert Systems with Applications (16.13%), followed by IEEE Access (12.90%). The remaining articles are dispersed among other journals in the fields of computer science, industrial engineering, and operations management.

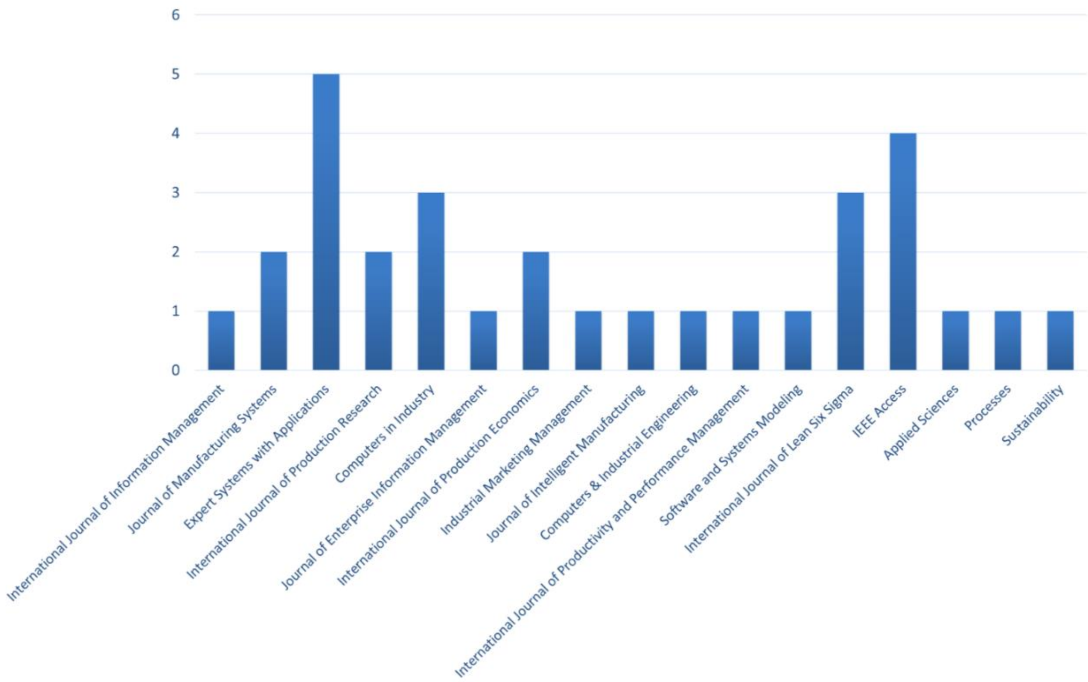

Figure 8. Number of Articles in Different Journals

The geographical distribution of the contributing countries is presented in Figure 9. According to the figure, 24 different countries have contributed to these studies. The highest number of published articles originates from Germany (22.58%), followed by Italy and Brazil (12.90% each), Hong Kong and Iran (9.68% each), Austria, Indonesia, South Korea, France, and the Czech Republic (6.45% each), and Portugal, Hungary, China, Belgium, Turkey, the Netherlands, Australia, the United States, the United Kingdom, Switzerland, Venezuela, Colombia, Vietnam, and Singapore (3.23% each). It is worth noting that some articles are the result of collaborative studies between multiple countries.

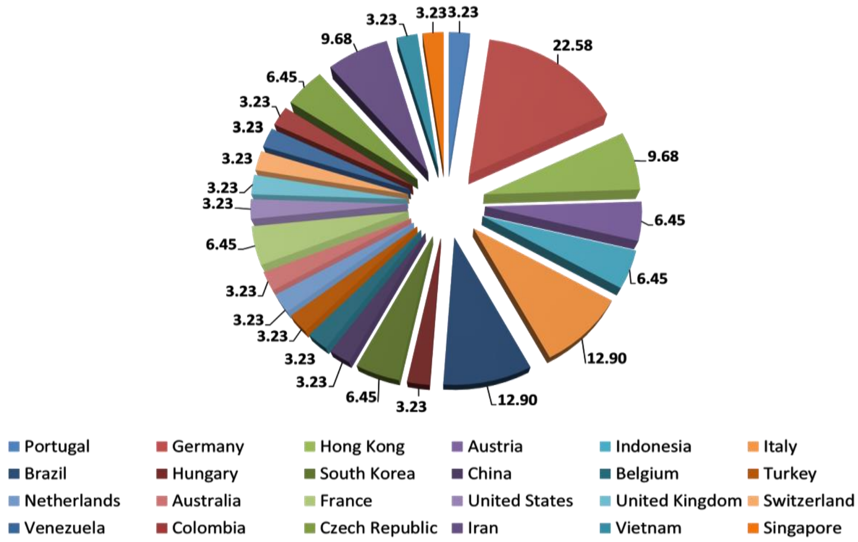

Figure 9. Distribution Percentage of Selected Articles in Different Countries

5-2) Classification of Articles by SC Domain

A classification of the selected articles based on the SC domain to which they primarily contribute is presented in this subsection. Drawing upon the eleven thematic domains identified in the literature review— namely SC, Logistics, Inventory Management/control, Demand Forecasting, Supplier Selection, Production, R&D, Marketing, Sales, Buy, and Customer Service —the analysis maps the distribution of PM applications across the SC ecosystem.

Table 8. Classification of Articles by SC Domain

Rows	SC domain	References
1	SC	(Bodendorf et al., 2023), (Ramires et al., 2022)
2	Logistics	(Aloini et al., 2020), (Y. Wang et al., 2014), (Zerbino et al., 2019), (S. k. Lee et al., 2013), (Knoll et al., 2019), (Kermani et al., 2024)
3	Inventory Management/control	
4	Demand forecasting	
5	Supplier selection	
6	Production	(Tran et al., 2021), (Khakpour et al., 2025b), (Khakpour et al., 2025a), (Monti et al., 2024), (Er et al., 2018), (Rudnitckaia et al., 2022), (Lau, Ho, Chu, et al., 2009), (Lugaresi et al., 2023), (J. Park et al., 2014), (Sánchez et al., 2020), (Celik et al., 2025), (May et al., 2024), (Lorenz et al., 2021), (Choueiri et al., 2021b), (Loacker et al., 2025), (C. K. H. Lee et al., 2016), (W. M. P. van der Aalst et al., 2024), (Choueiri et al., 2021a), (Choueiri et al., 2020), (Ruschel et al., 2021), (Novák et al., 2022)
7	R&D	
8	Marketing	
9	Sales	(Tridalestari et al., 2023)
10	Buy	
11	Customer Service	(Lau, Ho, Zhao, et al., 2009)

Of the reviewed articles, the majority focus is on the production domain (67.74%), followed by logistics (19.35%), as presented in Figure 10. The remaining articles are distributed across SC (6.45%), sales (3.23%), and customer service (3.23%).

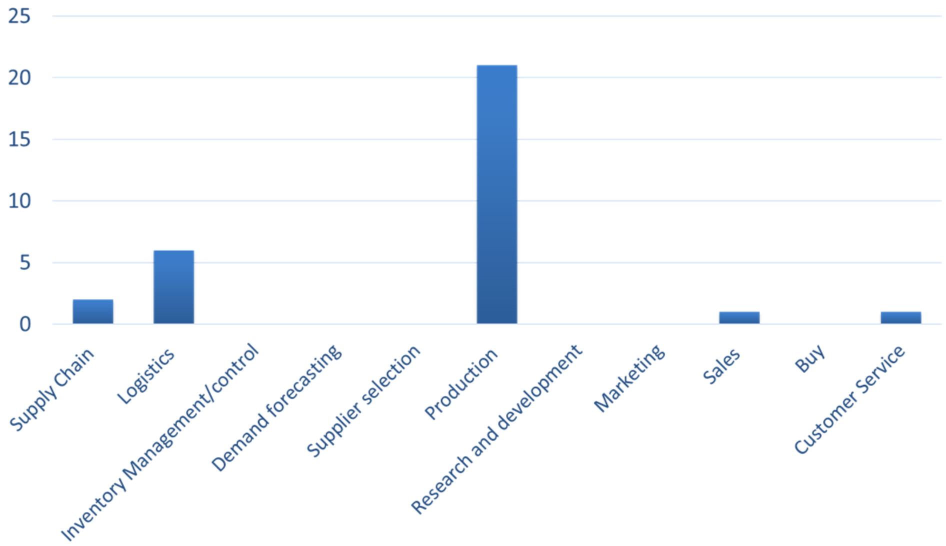

Figure 10. Distribution of SC Domains in the Selected Articles

5-3) PM Methods in Selected Articles

The selected articles are categorized according to the different methods and stages of PM in Table 9.

Table 9. PM Methods in Selected Articles

Rows	Method	References
1	Discovery	(Tridalestari et al., 2023), (Khakpour et al., 2025b), (Loacker et al., 2025), (Choueiri et al., 2021b), (Lorenz et al., 2021), (May et al., 2024), (Celik et al., 2025), (Sánchez et al., 2020), (J. Park et al., 2014), (Lugaresi et al., 2023), (Lau, Ho, Chu, et al., 2009), (S. k. Lee et al., 2013), (Rudnitckaia et al., 2022), (Zerbino et al., 2019), (Y. Wang et al., 2014), (Er et al., 2018), (Bodendorf et al., 2023), (Aloini et al., 2020), (Khakpour et al., 2025a), (Tran et al., 2021), (Ruschel et al., 2021), (Choueiri et al., 2020), (Lau, Ho, Zhao, et al., 2009), (Choueiri et al., 2021a), (Knoll et al., 2019), (Ramires et al., 2022), (W. M. P. van der Aalst et al., 2024), (Kermani et al., 2024)
2	Conformance checking	(Tridalestari et al., 2023), (Khakpour et al., 2025b), (Lorenz et al., 2021), (J. Park et al., 2014), (Y. Wang et al., 2014), (Knoll et al., 2019), (Kermani et al., 2024)
3	Enhancement	(Khakpour et al., 2025b), (C. K. H. Lee et al., 2016), (Lorenz et al., 2021), (J. Park et al., 2014), (Lau, Ho, Chu, et al., 2009), (Zerbino et al., 2019), (Y. Wang et al., 2014), (Bodendorf et al., 2023), (Monti et al., 2024), (Aloini et al., 2020), (Novák et al., 2022), (Choueiri et al., 2020), (Lau, Ho, Zhao, et al., 2009), (Choueiri et al., 2021a), (Kermani et al., 2024)
4	Above methods combination	(Tridalestari et al., 2023), (Khakpour et al., 2025b), (Lorenz et al., 2021), (Lau, Ho, Chu, et al., 2009), (Zerbino et al., 2019), (J. Park et al., 2014), (Y. Wang et al., 2014), (Bodendorf et al., 2023), (Aloini et al., 2020), (Choueiri et al., 2020), (Lau, Ho, Zhao, et al., 2009), (Choueiri et al., 2021a), (Knoll et al., 2019), (Kermani et al., 2024)

As shown in Figure 11, discovery was the most frequently used method (28 articles). Enhancement ranked second (15 articles), followed by conformance checking with 7 articles.

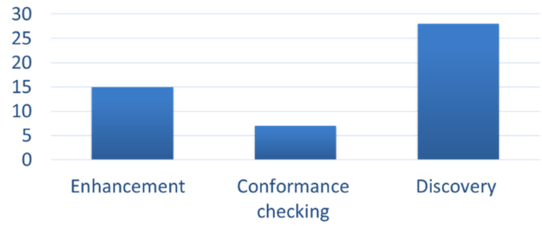

Figure 11. The Frequency of PM Methods Adoption in Selected Articles

As shown in Figure 12, some articles employed a combination of methods.

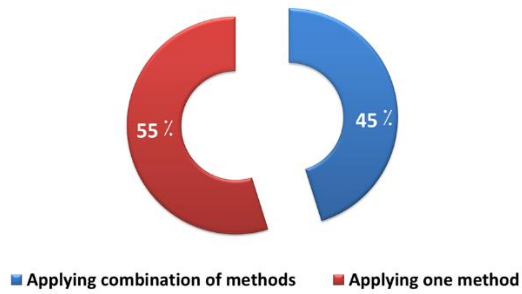

Figure 12. Percentage of Single and Combined Methods of PM in Selected Articles

Algorithms Run in Selected Articles

The classification of the selected articles based on different PM algorithms is presented in Table 10.

Table 10. PM Algorithms Applied in Selected Articles

Rows	Algorithms	Reference
1	GM	
2	AM	(Rudnitckaia et al., 2022), (Choueiri et al., 2021b), (Tridalestari et al., 2023)
3	FM	(Aloini et al., 2020), (Er et al., 2018), (Y. Wang et al., 2014), (Rudnitckaia et al., 2022), (Zerbino et al., 2019), (Tridalestari et al., 2023), (Choueiri et al., 2020), (Ruschel et al., 2021),
4	IM	(Bodendorf et al., 2023), (Rudnitckaia et al., 2022), (Tridalestari et al., 2023), (May et al., 2024), (Celik et al., 2025), (Knoll et al., 2019), (Choueiri et al., 2021a)
5	HM	(Er et al., 2018), (Y. Wang et al., 2014), (Tridalestari et al., 2023), (May et al., 2024), (Choueiri et al., 2021a), (Ruschel et al., 2021)
6	Other	(Khakpour et al., 2025b), (Lugaresi et al., 2023), (Khakpour et al., 2025a), (Lau, Ho, Chu, et al., 2009), (Monti et al., 2024), (S. k. Lee et al., 2013), (J. Park et al., 2014), (Lorenz et al., 2021), (C. K. H. Lee et al., 2016)
7	Software only	(Novák et al., 2022), (Kermani et al., 2024), (Ramires et al., 2022), (W. M. P. van der Aalst et al., 2024), (Loacker et al., 2025), (Sánchez et al., 2020), (Tran et al., 2021)

As observed in Figure 13, the "Other" category shows the highest frequency (9 articles), followed by the FM algorithm (8 articles), "Software only" approaches (7 articles), the IM algorithm (7 articles), and the HM algorithm (6 articles). The AM algorithm appears in 3 articles, while no articles exclusively employing the GM algorithm were identified.

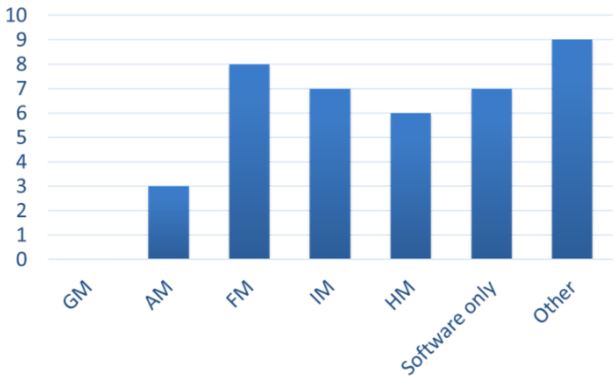

Figure 13. The Frequency of PM Algorithms Applied in the Selected Articles

It is important to note that some articles employed a combination of multiple algorithms, which explains why the sum of frequencies exceeds the total number of articles reviewed.

PM Tools Applied n Selected Articles

The process analysis tools applied in the selected articles are presented in Table 11.

Table 11. PM Tools Applied in Selected Articles

Rows	Software	Reference	Platform	Some of the Abilities	Description
1	ProM	(Aloini et al., 2020), (Er et al., 2018), (Y. Wang et al., 2014), (Rudnitckaia et al., 2022), (Lorenz et al., 2021), (Celik et al., 2025), (Knoll et al.,	Desktop	1- Process discovery 2- Conformance checking 3- Performance-based PM 4- Organizational Mining 5- Process Monitoring	1- Open source and plugin oriented 2- The ability to extract process data from the organization's information systems 3- Supporting HM, GM, FM, etc. (Er et al., 2018; Kedem-Yemini, 2020)

Rows	Software	Reference	Platform	Some of the Abilities	Description
		2019), (Novák et al., 2022)		6- Event logs etc. (G. Park et al., 2024)	http://www.ProMtools.org
2	Disco	(Aloini et al., 2020), (Tran et al., 2021), (Er et al., 2018), (Rudnitckaia et al., 2022), (Zerbino et al., 2019), (Lorenz et al., 2021), (Celik et al., 2025), (Knoll et al., 2019), (Choueiri et al., 2020), (Ruschel et al., 2021)	Desktop	1- Process discovery 2- Performance-based PM 3- Variant Analysis 4- PM Framework, Guideline, & Tool 5- Event logs 6- PM Visualization (G. Park et al., 2024)	1- Simple user intermediate able to automatically form flowcharts from log files 2- Easy analysis of process data without requiring deep technical knowledge (Kedem-Yemini, 2020) 3- The upgraded FM version is applied as a key feature to extract process maps (Mahendrawathi et al., 2017; Zerbino et al., 2018) www.fluxicon.com
3	Celonis	(Khakpour et al., 2025a), (Sánchez et al., 2020), (Khakpour et al., 2025b), (Ramires et al., 2022)	Under the web	1- Process discovery 2- Conformance checking 3- Performance-based PM 4- Organizational Mining 5- Process Monitoring 6- Predictive Process Monitoring 7- Process Model Repair 8- Event logs, etc. (G. Park et al., 2024)	1- A set of trade solutions and components 2- The ability to continuously supervision and monitor the processes in real-time 3- The capability to integrate PM with AI and ML for generating highly intelligent and fully automated insights from data logs (Kedem-Yemini, 2020) https://www.celonis.com
4	Microsoft PAFnow		Desktop	1- Process discovery 2- Process Reconstruction 3- Event logs (Kurganov et al., 2021)	1- Based on the Microsoft Power BI platform 2- The ability to connect to different systems, including ERP and CRM systems https://www.microsoft.com
5	PM4PY	(Loacker et al., 2025), (May et al., 2024), (Choueiri et al., 2021a)	Library functions	1- Process discovery 2- Conformance checking (Rabbi et al., 2024)	1- An open-source library function in the Python programming language 2- Support for alpha plus, induction, and exploration miners (Rabbi et al., 2024) 3- The possibility of easy integration of PM algorithms with other algorithms in data science (Berti et al., 2019) http://python.org
6	RapidMiner	(Rudnitckaia et al., 2022)	Desktop	RapidProM: 1- Modeling and executing analytical workflows 2- Access to text mining, web mining,	1- Open source 2- Graphical workflow with 500+ operators (Moreira et al., 2025)

Rows	Software	Reference	Platform	Some of the Abilities	Description
				and deep learning tools via the Marketplace 3- Data management and conversion capabilities 5- Event logs (Aalst et al., 2017)	
7	E-mail Interaction Miner	(W. M. P. van der Aalst et al., 2024)	Desktop	1- E-mail-driven business processes 2- Exposing collaboration problems 3- Identifying improvement opportunities for future projects (W. M. P. van der Aalst et al., 2024)	This software works with Microsoft Outlook.
8	Behalfab	(Kermani et al., 2024)	Under the web (Cloud and On Premise)	1- Process Discovery (Kermani et al., 2024) 2- Performance analysis and monitoring 3- Communication network analysis 4- Conformance checking 5- improvement 6- AI-powered process performance analysis 7- AI-based interpretation of process performance and identification of improvement potentials 8- AI-driven suggestions for improving process performance https://behfalab.com/	https://behfalab.com/
9	Not mentioned	(Monti et al., 2024), (Bodendorf et al., 2023), (S. k. Lee et al., 2013), (Lau, Ho, Chu, et al., 2009), (Lugaresi et al., 2023), (J. Park et al., 2014), (Choueiri et al., 2021b), (C. K. H. Lee et al., 2016), (Tridalestari et al.,			

Rows	Software	Reference	Platform	Some of the Abilities	Description
		2023), (Lau, Ho, Zhao, et al., 2009)			

As shown in Figure 14, the most widely used tool was Disco (10 articles), followed by ProM (8 articles). Celonis ranked third (4 articles), and the Python library PM4PY appeared in 3 articles. Other tools, such as RapidMiner and E-mail Interaction Miner, each appeared in one article. Additionally, the emerging tool Behalfab was also featured in one article, representing the first and only Iranian homegrown PM tool in the Middle East. In contrast, Microsoft PAFnow recorded no usage. Furthermore, 10 articles did not mention a specific tool.

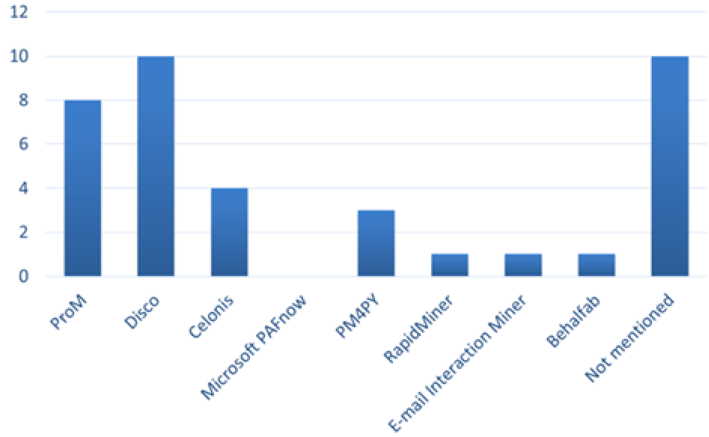

Figure 14. The Number of Exploration Algorithms Applied in Selected Articles

5-6) Objectives and Challenges of Selected Articles

This subsection examines the objectives and challenges reported in the selected articles. The identified challenges are classified according to the five-layer analytical framework proposed in this study. Each of these five main layers is further delineated into a set of sub-layers, resulting in a total of sixteen distinct categories that capture the granular aspects of PM challenges in the SC. The results of this classification are presented in Table 12.

Table 12. Objectives and Challenges of Selected Articles

Rows	Reference	Objective	challenges				
			Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
1	(Aloini et al., 2020)	PM application for maritime logistics process analysis and improvement through integration with social network analysis and text mining techniques	A1, A2, A3	B1	C1	D1, D3	E2
2	(Choueiri et al., 2020)	PM application for remaining time prediction in manufacturing systems to enhance production planning and customer feedback reliability			C2		
3	(Choueiri et al., 2021a)	PM for manufacturing dependency discovery			C1	D3	
4	(Knoll et al., 2019)	PM application for internal logistics process analysis and	A1	B3	C1	D1	E1, E4

Rows	Reference	Objective	challenges Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
		improvement through multidimensional value stream mapping					
5	(Lorenz et al., 2021)	PM application for manufacturing production process analysis and improvement	A2, A3	B2, B3			E2, E3
6	(Lugaresi et al., 2023)	PM application for automated digital twin generation in complex manufacturing systems with assembly operations	A1, A3	B1, B2, B3		D1, D2, D3	E1
7	(Sánchez et al., 2020)	PM application for manufacturing process self-supervision and failure detection in Industry 4.0 context	A1, A2, A3	B1, B2	C1, C2, C3	D1, D2, D3	E1, E2, E3
8	(W. M. P. van der Aalst et al., 2024)	Expanding PM from workflow-based to object-centric approaches using production and logistics concepts	A2, A3	B1	C1, C3	D1	E2, E3
9	(Er et al., 2018)	PM application for production planning process analysis and improvement		B1	C2	D3	E4
10	(May et al., 2024)	Automated simulation model generation framework for production systems using PM and machine learning techniques	A1	B3	C2, C3	D3	E1, E3
11	(J. Park et al., 2014)	PM application for ship block manufacturing process performance evaluation and improvement	A1, A2	B2			E1, E2
12	(Bodendorf et al., 2023)	PM application for SC integration to overcome barriers of organizational compatibility, planning, and information sharing through intelligent systems	A1, A3	B1	C3	D1, D3	E2, E4
13	(Lau, Ho, Zhao, et al., 2009)	PM application for discovering fuzzy association rules to identify relationships between process parameters and customer satisfaction in SC networks	A1	B3		D1, D3	E1
14	(Choueiri et al., 2021b)	PM application for multi-product scheduling and production planning optimization		B3		D1	E2
15	(Y. Wang et al., 2014)	PM application for logistics process analysis and improvement	A1	B2	C1		E3

Rows	Reference	Objective	challenges				
			Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
16	(C. K. H. Lee et al., 2016)	Fuzzy association rule mining integrated with variable-length genetic algorithm for garment production process optimization and quality assurance		B3	C1, C2, C3		E1
17	(S. k. Lee et al., 2013)	PM application for after-assembly block manufacturing process analysis and improvement	A1, A3	B1, B2	C1	D1	E1, E4
18	(Lau, Ho, Chu, et al., 2009)	Fuzzy association rule mining for manufacturing process quality analysis		B2	C2, C3		E1, E2, E3
19	(Ruschel et al., 2021)	PM application for manufacturing process performance analysis and time prediction	A1	B3	C1, C2, C3	D1, D3	E1
20	(Loacker et al., 2025)	PM application for quality management enhancement in food processing operations	A1, A3	B1	D3		E1, E4
21	(Monti et al., 2024)	PM application for smart manufacturing process analysis and improvement	A1, A3	B1, B3	C2	D1, D2	E1, E4
22	(Ramires et al., 2022)	PM application for procurement process analysis and improvement within a hospital SC	A3, A1			D1	E2, E4, E1
23	(Rudnitckaia et al., 2022)	PM application for manufacturing process analysis and bottleneck detection with root cause identification	A1, A2, A3	B1, B3	C1, C2	D1, D2	E1, E2, E3, E4
24	(Khakpour et al., 2025b)	PM application for manufacturing process analysis and improvement	A1, A2	B1	C2	D2, D3	E1, E2, E4
25	(Khakpour et al., 2025a)	PM application for manufacturing process analysis and defect prediction to improve sustainability	A1, A2		C2	D3	E1, E2, E4
26	(Zerbino et al., 2019)	PM application for freight export process analysis and improvement in maritime logistics	A1, A3	B3	C1	D3	E1, E2, E3, E4
27	(Celik et al., 2025)	PM application for assemble-to-order manufacturing process analysis and improvement	A1, A3	B2, B3	C1	D1, D3	E1, E2, E3, E4
28	(Tridalestari et al., 2023)	PM application for consumer behavior analysis in omnichannel distribution systems	A3	B3	C3		E2
29	(Tran et al., 2021)	PM application for manufacturing process	A1, A2, A3	B3	C1		E1, E3

Rows	Reference	Objective	challenges Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
		analysis and improvement using indoor positioning systems data					
30	(Kermani et al., 2024)	PM application for procurement process analysis and improvement	A1, A3	B1			E2, E4
31	(Novák et al., 2022)	PM application for production process analysis and enhancement	A2	B3	C3	D1	E3

Figure 15 illustrates the distribution of challenges across the five main layers. The inter-organizational coordination and sustainability layer accounts for 29 challenge occurrences, representing the highest frequency among all layers. The process modeling layer follows with 27 occurrences. The data integration layer ranks third with 25 occurrences. The analytics and prediction layer comprises 24 occurrences, while the operational scalability and real-time layer shows the lowest frequency with 21 occurrences.

Figure 15. The Number of Exploration Algorithms Applied in Selected Articles

A more detailed examination of the sixteen sub-layers reveals the following distribution across each main layer. Within the data integration layer, data quality and completeness is the most frequently cited challenge with 21 occurrences, followed by integration of data sources with 16 occurrences, while data collection and infrastructure accounts for 10 occurrences. In the process modeling layer, model complexity is identified in 15 articles, level of abstraction and granularity appears in 12 articles, and semantic gap is discussed in 8 articles. Within the analytics and prediction layer, classification and detection accuracy appears in 13 articles, followed by prediction and uncertainty with 11 occurrences, while model quality is discussed in 9 articles. In the operational scalability and real-time layer, scalability and efficiency accounts for 15 occurrences, generalization and transfer appears in 13 articles, and real-time processing shows the lowest frequency across all sub-layers with only 5 occurrences. Within the inter-organizational coordination and sustainability layer, human factors and expertise is identified in 19 articles, followed by organization and stakeholders with 16 occurrences; SC and value chain appears in 13 articles, and governance, privacy, and standards accounts for 11 occurrences.

6) Discussion

Following a comprehensive review and content analysis of the selected articles, the relevant data were extracted to address the research questions. Accordingly, each research question is answered in the subsequent sections.

RQ1: The upward trend in publications since 2019, as shown in Figure 6, suggests that the application of the PM method is gaining momentum in managing and improving efficiency across various fields of the SC in recent years. This increase may be attributed to a growing recognition of the method's potential or to recent advancements that have facilitated its implementation in diverse SC contexts. The finding that all reviewed articles are sourced from journals (Figure 7) is noteworthy. A possible explanation for this predominance is the relative novelty of the research topic, which has garnered significant attention in recent years. This surge in interest likely leads high-impact journals to show greater willingness to publish related studies. Furthermore, journal articles generally tend to receive higher citation counts and are often perceived as more authoritative compared to conference proceedings, which may further encourage researchers to target journals for disseminating work in this emerging field. The distribution of the reviewed articles across various journals, as illustrated in Figure 8, indicates the interdisciplinary nature of PM research in the SC. The prominence of the journal Expert Systems with Applications suggests that it serves as a primary outlet for studies applying data-driven techniques to practical SC problems. Furthermore, the high representation of the journal IEEE Access may be attributed to its broad technological scope and open-access model, which facilitates the rapid dissemination of research in an emerging field like PM.

RQ2: The predominance of German research in the field of PM within SC management, as depicted in Figure 9, can be attributed to the country's strong industrial base and its pioneering role in Industry 4.0—a concept originating in Germany that encompasses data-driven tools such as big data analytics (Gyarmathy et al., 2025) and PM for the analysis and optimization of SC operations. Within this paradigm, PM serves as a fundamental tool for analyzing event logs to enhance transparency and efficiency by enabling data-driven analysis and optimization of production and logistics processes. The study, for instance, draws on interviews with German manufacturing firms and highlights the practical application of PM in production and logistics within the context of Industry 4.0 (Dunzer et al., 2025). Recent scholarly work from Kühne Logistics University in Hamburg substantiates this development by systematically identifying and validating key use cases for PM in SC operations. This research highlights how techniques such as object-centric mining and federated PM can uncover inefficiencies across multi-tier supply networks, thereby providing a robust foundation for the digital transformation goals central to Industry 4.0 (Oldenburg et al., 2025).

RQ3: The observed distribution in Figure 10, with a strong emphasis on production and logistics, reflects the nature of PM as a process-oriented analytical tool. One reason for this concentration could be that production processes generate highly structured event logs from machinery and information systems—a characteristic that makes them particularly conducive to PM analysis (Stefanovic et al., 2020). Furthermore, production constitutes the operational core of the SC, with its efficiency directly determining the performance of downstream logistics activities. The strong representation of production-focused studies in the literature reflects both the data availability in manufacturing settings and the foundational role of production processes in overall SC performance. Further studies conducted in production and logistics are as follows: Dunzer et al. (2025); Kurniasih et al. (2024); and Napieraj et al. (2025).

RQ4: The distribution of PM methods and stages in Figure 11 follows the natural progression of PM projects, from foundational discovery to advanced analysis. Discovery, as the most frequently used method, serves as the essential starting point for understanding actual processes. The prevalence of this method underscores its foundational role in PM research. Enhancement, ranking second, reflects the practical need to optimize and extend process models once the initial discovery is complete. The lower frequency of conformance checking (7 articles) is likely due to its specialized nature, which requires predefined models for comparison and validation. The use of combined methods by some articles, as illustrated in Figure 12, demonstrates the growing methodological sophistication in the field. The distribution of algorithm usage in Figure 13 reveals distinct patterns in PM research. The high frequency of the 'Other' category (9 articles) indicates the diversity and fragmentation of the PM landscape, where many researchers employ customized, hybrid, or emerging algorithms tailored to specific domain requirements. The FM algorithm, as the most frequently used standard algorithm (8 articles), represents a mature and well-established approach, with its popularity attributable to its effectiveness in discovering process models and its widespread implementation in commercial tools. The significant presence of 'Software only' approaches (7 articles) reflects the growing maturity and accessibility of commercial PM platforms, which provide out-of-the-box capabilities without requiring deep algorithmic implementation. The IM algorithm (7 articles) and HM algorithm (6 articles) maintain moderate usage as established techniques. In contrast, the limited adoption of AM (3 articles) and the complete absence of GM suggest that these algorithms may be less suitable for contemporary PM challenges or have been superseded by more efficient alternatives. The overlap in algorithm usage, where some articles employed a combination of multiple algorithms, reflects the complex nature of PM research, where hybrid approaches are often necessary to address multifaceted analytical challenges. Overall, this distribution reflects the field's evolution toward algorithms that better handle noise, incompleteness, and large-scale event data. As shown in Figure 14, an analysis of the reviewed studies reveals a clear hierarchy in the adoption of PM tools. Disco, as the most widely used tool (10 articles), is favored for its intuitive interface and rapid visualization capabilities, making it ideal for quick discoveries. ProM (8 articles) remains the platform of choice for advanced, algorithm-heavy analyses, reflecting its role as the academic standard in the field. The lower frequency of Celonis (4 articles) potentially reflects academic access limitations to this enterprise solution. The presence of PM4PY (3 articles) indicates a growing trend toward programmatic, flexible analysis. The appearance of Behalfab, as the first and only Iranian homegrown PM tool in the Middle East, leveraging artificial intelligence for the discovery, analysis, and data-driven improvement of organizational processes, highlights emerging regional contributions to the field. The absence of Microsoft PAFnow and the fact that 10 articles did not mention a specific tool suggest a focus on theoretical concepts or the use of non-specialized software in some studies. It is also worth noting that some articles employed a combination of multiple tools within a single study, leveraging the strengths of different software for various stages of analysis—for instance, using Disco for initial process discovery and ProM for more advanced conformance checking. This hybrid approach reflects a growing methodological maturity in the field. Overall, this distribution underscores a preference for either highly accessible tools like Disco or deeply functional platforms like ProM within the research community, while also highlighting the early-stage adoption of emerging tools and the increasing use of integrated, multi-tool strategies.

RQ5: The distribution of challenges across the five main layers reveals important insights about the current state of PM research in SC contexts (Figure 15).

The disproportionate distribution of challenges across thematic layers in the literature provides valuable insights into the evolving research priorities within the field. The notably high number of challenges identified within the inter-organizational coordination and sustainability layer (29 articles) is particularly striking. This predominance signals a critical and persistent area of concern, suggesting that the complexities inherent in aligning multiple stakeholders represent a primary obstacle to effective PM implementation in SCs. The frequency with which these cross-organizational and human-related challenges appear in the literature underscores that such obstacles are not merely technical but are deeply rooted in organizational dynamics. This prevalence is logically explained by the fundamental nature of SCs as networks of independent entities; achieving consensus on data governance, sustainability protocols, and strategic objectives is inherently more intricate in such multi-organizational settings, thereby generating a wider array of reported challenges.

The substantial number of challenges in the process modeling layer (27 articles) underscores the persistent difficulties in accurately capturing SC processes through PM techniques. SC processes often involve parallel activities, exceptions, and non-linear flows that challenge conventional modeling approaches. This finding suggests that existing process modeling notations and algorithms may require further adaptation to adequately represent the complexity of real-world SC operations. The frequency of these challenges is logically high because SC processes frequently span multiple organizations and geographies, resulting in process variations that standard modeling techniques, often designed for more predictable and contained workflows, struggle to accommodate.

The data integration layer (25 articles) confirms that data-related issues remain fundamental barriers to PM adoption in multi-organizational settings. This aligns with the well-documented challenges of data heterogeneity, incompleteness, and quality issues in SC contexts where data originates from diverse systems across organizational boundaries. The prominence of data quality and integration challenges indicates that foundational data management capabilities are essential prerequisites for successful PM initiatives. The significant number of studies focusing on this layer is unsurprising, as the very nature of SCs—comprising disparate systems such as ERPs, WMS, and TMS operated by different parties—inevitably creates data silos and inconsistencies that must be resolved before any meaningful analysis can occur.

The analytics and prediction layer (24 articles) highlights the growing emphasis on predictive capabilities and analytical precision in contemporary PM research. The relatively balanced focus on classification accuracy and prediction reflects the dual role of PM in both understanding past behavior and anticipating future outcomes. However, the slightly lower number of challenges compared to foundational layers indicates that advanced analytics often build upon resolved challenges in data integration and process representation. The moderate count in this layer can be explained by the maturity progression of the field; interest in sophisticated analytics naturally follows, rather than precedes, the establishment of reliable data foundations and process models.

The operational scalability and real-time processing layer presents the fewest challenges (21 articles), with real-time processing being particularly sparse (5 articles). This distribution can be attributed to the maturation of foundational technologies and methodologies in this domain. Unlike data integration or model accuracy issues that dominate earlier stages of PM maturity, real-time processing challenges have been substantially mitigated through advances in stream processing frameworks (e.g., Apache Kafka, Flink), edge computing capabilities, and the widespread adoption of microservices architectures that inherently support scalability. Furthermore, commercial PM tools have progressively embedded real-time monitoring features as standard offerings, effectively addressing many deployment hurdles that might have warranted dedicated research attention in the past. The relatively low research focus may also reflect a pragmatic industry reality—while real-time visibility is increasingly demanded, many organizations still derive sufficient value from near-real-time or batch processing for most SC operational decisions, making the incremental investment in genuine real-time capabilities justifiable only for specific high-velocity use cases. Therefore, the underrepresentation of this category likely signals problem mitigation through practical solutions rather than neglect, with research efforts justifiably concentrating on more persistent foundational challenges where academic contributions can yield greater marginal impact.

The granular analysis of sub-layers provides deeper insights into specific challenge areas within each main layer.

Within the data integration layer, the predominance of data quality and completeness challenges (21 articles) confirms that incomplete, noisy, and low-quality event logs represent a primary barrier to effective PM in SCs. This finding calls for more research on data cleaning, imputation, and quality assessment techniques specifically designed for SC event data. The substantial frequency of integration of data sources challenges (16 articles) reflects the difficulty of consolidating data from disparate systems across organizational boundaries, including ERP systems, WMSs, and TMSs. The relatively lower number of data collection and infrastructure challenges (10 articles) may suggest that organizations have made progress in establishing basic data collection infrastructure, or alternatively, that infrastructure challenges are under-reported in academic literature compared to practitioner concerns. This disparity could be attributed to the fact that while basic data collection mechanisms (e.g., barcode scanning, RFID) are now widely adopted in industry, the subsequent steps of ensuring quality and achieving seamless integration present more persistent and intellectually challenging problems that attract greater research attention.

In the process modeling layer, the prominence of model complexity challenges (15 articles) reflects the ongoing tension between comprehensive process representation and model interpretability. Researchers frequently grapple with the trade-off between capturing all process variations and maintaining models that remain useful for analysis and decision-making. The presence of level of abstraction and granularity challenges (12 articles) indicates ongoing debates about the appropriate level of detail for process representation in SC contexts, where processes often span multiple organizational units and time horizons. The lower number of semantic gap challenges (8 articles) may indicate either growing maturity in domain alignment between PM researchers and SC practitioners, or under-recognition of this issue in current research. The relatively lower count for semantic gap could be explained by the increasing availability of domain-specific ontologies and standards that help bridge the communication divide, or perhaps because this issue is often subsumed within broader discussions of model interpretability and stakeholder engagement found in other layers.

The analytics and prediction layer shows a relatively balanced distribution across its sub-layers. Classification and detection accuracy challenges (13 articles) and prediction and uncertainty challenges (11 articles) reflect the dual focus on both descriptive and predictive analytics in PM research. The slightly lower attention to model quality challenges (9 articles) can be reasonably explained by the relative maturity of foundational quality assurance frameworks in this domain. Unlike more emergent challenges requiring specialized adaptation to SC contexts, core model quality assessment has benefited from well-established methodologies, standardized validation techniques, and comprehensive quality metrics that have been progressively refined through years of research in both PM and broader data mining communities. Furthermore, many model quality considerations are now implicitly embedded within mainstream analytical applications and commercial tools, where quality checks have become standardized components rather than standalone research topics. The SC domain specifically has been able to leverage and adapt these general-purpose quality frameworks effectively, reducing the need for dedicated investigations into fundamental model quality issues. This distribution does not indicate neglect but rather reflects a natural research progression where foundational concerns, once substantially addressed, receive proportionally less attention as the field advances toward more specialized and context-specific challenges. The balanced distribution across other sub-layers further confirms that research efforts are appropriately diversified, with attention justifiably concentrated on areas where SC contexts introduce unique complexities that demand novel methodological contributions.

Within the operational scalability and real-time layer, the dominance of scalability and efficiency challenges (15 articles) highlights the computational challenges of applying PM algorithms to large-scale SC event data, which often involves millions of events across multiple organizations. The high number of generalization and transfer challenges (13 articles) indicates a significant gap, that PM models developed in one SC context may not directly apply to others, and calls for research on transfer learning and domain adaptation techniques that account for varying process configurations across different SC settings. The very low number of real-time processing challenges (5 articles) represents a relative maturity in this domain. This low number might indicate that existing approaches for handling streaming data in PM exhibit greater stability compared to scalability and generalizability. Conversely, the increased adoption of event-driven architectures and low-latency communication technologies in modern SCs, which inherently support the streaming and timely analysis of data, could be another contributing factor.

In the inter-organizational coordination and sustainability layer, the dominance of human factors and expertise challenges (19 articles) and organization and stakeholders challenges (16 articles) confirms that PM implementation in SCs is fundamentally a socio-technical endeavor. Technical solutions alone are insufficient without addressing user training, organizational readiness, and stakeholder alignment across organizational boundaries. The presence of SC and value chain challenges (13 articles) indicates growing attention to how PM can support broader SC integration and value creation, beyond isolated process improvements. The inclusion of governance, privacy, and standards challenges (11 articles) reflects ongoing concerns about data ownership, sharing agreements, and interoperability standards in multi-organizational settings—issues that become particularly salient when PM spans organizational boundaries. The high number of human and organizational challenges can be explained by the fundamental nature of SCs as socio-technical systems where trust, negotiation, and relational governance are as critical as technical infrastructure. Conversely, the slightly lower but still significant attention to governance and standards may reflect the difficulty of conducting research on these sensitive topics, which often involve confidential information and legal arrangements not easily accessible to academic scrutiny.

RQ6: The distribution of challenges across the five main layers establishes a foundation for identifying targeted solutions. Recent advances in PM, artificial intelligence, and data science provide promising methods for addressing these obstacles, while insights from organizational science and inter-organizational governance offer complementary approaches.

Data Integration Layer Solutions

To address the persistent challenge of incomplete, noisy, and low-quality event logs in SC contexts, recent research has developed sophisticated approaches for multimodal data integration and intelligent event log construction.

Reference Architecture for Multimodal Event Log Construction: A reference architecture for constructing event logs from multimodal data is proposed, specifically designed to overcome the limitations of current applications that primarily rely on (semi-)structured data from process-aware information systems. This architecture integrates diverse data types, construction functions, and PM use cases, leveraging state-of-the-art generative AI to extract event log data from unstructured sources such as videos, documents, and bot logs. Following a design science research methodology, the architecture is evaluated through a software artifact using real-world IT service management data, providing a framework for incorporating the full range of real-world data available in complex operational environments (Leimeister et al., 2025).

Multimodal Event Log Enrichment: To address data quality and completeness challenges, recent research proposes multimodal event log enrichment techniques (Aleksandar Gavric et al., 2025). The Business-knowledge Integration Cycles (BICycle) method and the mm_proc_miner tool convert raw unstructured data from video, audio, and sensor sources into structured event logs. This approach addresses the persistent problem of incomplete digital traces by capturing manual and physical work activities that traditional information systems fail to record—a challenge that prior research has conceptualized as "blind spots" in process analysis (Kratsch et al., 2022). Building upon foundational work in multimodal PM (A. Gavric et al., 2024) and video-to-log conversion, including reference architectures that bridge computer vision and PM, the method employs self-hosted joint embedding spaces to analyze semantic distances across modalities while preserving privacy and preventing AI hallucinations. This offers a solution for enhancing event log quality in SC contexts where physical operations generate limited digital footprints.

For the integration of data sources across organizational boundaries, federated PM frameworks have emerged as a principal solution. A recent study proposes a vertical federated PM framework that enables inter-organizational process discovery without requiring organizations to share raw sensitive data. The framework anonymizes local event logs and merges them into federated event logs using time minimization strategies to correlate events and generate global case identifiers (Iwan et al., 2025). This approach maintains privacy compliance while achieving comparable accuracy to centralized methods, directly addressing the integration challenges arising from disparate ERP, WMS, and TMS systems across SC partners.

Process Modeling Layer Solutions

To address the challenge of capturing complex SC processes with multiple interacting objects while maintaining model interpretability, object-centric PM has emerged as a transformative approach.

Addressing the inherent trade-off between comprehensive representation and interpretability in complex process models remains a critical challenge. Object-centric PM (OCPM) enables a more nuanced representation of complex SC processes by capturing interactions between multiple objects, thereby addressing this trade-off (Messal et al., 2025). The authors also highlight the evolution from case-centric to object-centric approaches as a key trend in PM research and practice.

Object-Centric PM for Interconnected Processes: A comprehensive case study on a real-life P2P process demonstrates the practical application of object-centric PM techniques to overcome the limitations of traditional case-centric approaches. The study extends the well-established project management methodology to the object-centric setting, providing clear guidance for practitioners implementing object-centric PM projects (Berti et al., 2025).

For model quality assessment, the integration of PM with simulation offers promising advances. Rather than building simulation models manually—a resource-intensive and static approach—recent methodologies enable simulation models to be mined directly from operational data. This allows for continuous validation and refinement of process models against actual SC behavior, addressing the need for supply-chain-specific quality metrics that account for inter-organizational dependencies, temporal constraints, and exception handling (Oldenburg et al., 2025).

Preliminary evidence from recent industry developments suggests that combining such object-based methodologies with agentic AI workflows could significantly improve return on investment. This integration would enable a more nuanced representation of parallel activities and non-linear flows characteristic of SC operations while maintaining model usability for decision-making.

Analytics and Prediction Layer Solutions

To address the challenge of anticipating future process behavior in dynamic SC environments, recent research has developed sophisticated predictive process monitoring techniques that account for inter-organizational dependencies and temporal uncertainties.

Predictive Process Monitoring for Collaborative Contexts: To enhance classification and detection accuracy while addressing prediction and uncertainty, recent extensions to predictive process monitoring have specifically targeted collaborative inter-organizational contexts. Propose an extension of traditional process prediction that accounts for the particularities of collaborative processes. The approach enables predictions about next activities per participant and anticipating inter-organizational message exchanges (Delgado et al., 2025). This approach facilitates early detection of deviations, violations, and delays, enabling preventive resource reallocation across organizational boundaries.

Operational Scalability and Real-Time Layer Solutions

To overcome the challenge of processing massive event data in SC contexts, new algorithms with distributed architectures and graph-based approaches have been developed.

Graph-based Scalable Algorithms: A recent study introduces a graph-based algorithm called GAITN (Graph Advanced Invisible Task in Non-free Choice) for high-scalability process discovery. This algorithm increases the volume of discoverable events by partitioning the event log and creating rules for merging partitions. Comparative results with GIT, α, and Fodina algorithms demonstrate that GAITN produces higher quality process models (in terms of fitness, precision, generalization, and simplicity) when confronted with high numbers of events, significantly improving the scalability of PM algorithms (Sungkono et al., 2023).

Integrated Frameworks with Low Computational Cost: The TGIPM (Timed Genetic-Inductive PM) algorithm combines Time Genetic PM and Inductive Mining algorithms within a unified framework. While recovering missing activities and ensuring structural correctness of process models, this algorithm maintains lower computational cost compared to sequential approaches and is highly suitable for large and incomplete datasets (Effendi et al., 2025).

Edge-based PM: An efficient edge-based process model discovery technique is introduced that addresses scalability challenges in IoT environments by bringing processing operations closer to data sources and avoiding full data centralization. Implementation of this method on the PM4Py open-source platform demonstrates that the technique significantly improves discovery efficiency while maintaining high model quality across nine public event logs (Su et al., 2025).

The research gap in real-time processing is being addressed through the emergence of AI and machine learning-based frameworks for real-time process monitoring.

Real-time Monitoring Frameworks with Deep Learning: A fully online, low-cost framework for real-time quality control in wire arc additive manufacturing (WAAM) is presented. In this approach, simultaneous voltage and current signals are transformed into spatial heatmaps and temporal Markov transition images, processed instantaneously by an optimized ResNet-18 neural network for layer-by-layer quality classification. Validation on the Invar dataset demonstrates accuracy up to 94% and inference times below 20 milliseconds per layer, enabling deployment in industrial environments (Fernández-Zabalza et al., 2025).

Domain Knowledge Integration for Adaptive Monitoring: The importance of explainable AI for intelligent and trustworthy process monitoring is emphasized. This approach, combining machine learning techniques with interpretable methods such as SHAP, enables real-time identification of anomaly causes and increases the reliability of real-time monitoring systems (Johannssen et al., 2025).

To overcome the challenge that PM models developed in one SC context may not directly apply to others, recent research has focused on developing hybrid methods and intelligent software platforms.

Integrated Software Platforms: ProcessM software is introduced as an intelligent PM solution that leverages container-based architecture (Docker) and modern databases (PostgreSQL and TimescaleDB) to provide easy deployment and scalability. This platform, supporting the specialized Process Query Language (PQL) for event log processing, represents a significant step toward standardization and generalization of PM techniques (Pawlak et al., 2025).

Simulation for Sparse Data Enrichment: A recent study proposes using discrete event simulation for modeling processes with sparse event logs. This approach, integrating data analysis and domain knowledge, generates richer synthetic data and enables the application of PM techniques in contexts where sufficient historical data is unavailable (Fairooz et al., 2025).

To ensure the effectiveness of scalable solutions, new evaluation methodologies have also been developed. A goal-oriented evaluation methodology for privacy-preserving PM (PPPM) is presented, comprising stages of objective establishment, targeted data acquisition, data refinement, log inspection, and PPPM analysis. This methodology, analyzing four real-world event logs from different domains, provides quantitative insights into the operational efficiency of privacy-preserving approaches and key errors affecting outcomes and time efficiency (Ileri et al., 2025).

Inter-Organizational Coordination and Sustainability Layer Solutions

Federated Conformance Checking for SCs: A privacy-aware federated conformance-checking approach is proposed that enables evaluating the correctness of cross-organizational process models, identifying miscommunications, and quantifying their costs. This approach addresses the distributed nature of inter-organizational collaborations where organizations work together to achieve shared goals requiring the exchange of information, goods, or services across boundaries. For evaluation, a simulated SC process is designed involving three organizations engaged in P2P, order-to-cash, and shipment processes. By generating synthetic event logs for each organization as well as for the complete process, the approach successfully identifies and evaluates the cost of pre-injected miscommunications while preserving the confidentiality of each organization’s internal processes. This represents the first federated conformance-checking approach that takes into account privacy and confidentiality concerns in inter-organizational settings (Rafiei et al., 2025).

Toward Data-Sovereign Inter-Organizational Process Monitoring: A holistic reference architecture is proposed to address the critical challenge of data fragmentation and privacy concerns in Industry 4.0 by integrating federated learning with sovereign data space concepts, such as GAIA-X and IDSA. The framework enables cross-company collaboration by allowing multiple industrial participants to collaboratively train AI models without sharing raw data, thereby preserving data sovereignty and security. The architecture leverages edge-fog-cloud computing to support distributed analytics and real-time condition monitoring. Validated through a predictive maintenance use case, the approach demonstrates that federated learning achieves accuracy comparable to centralized models while ensuring privacy and regulatory compliance. This work provides a foundational solution for secure, multi-party industrial IoT applications and establishes a practical pathway toward collaborative, privacy-preserving data ecosystems (Farahani et al., 2023).

More Suggestions for the Challenges Identified in This Study:

- Blockchain technology adoption in SCs positively influences trust through improved data accessibility, security, and transparent information sharing among partners (Zayed et al., 2026).
- Running mathematical optimization algorithms, including linear programming, combined with machine learning techniques such as regression models and ensemble methods (e.g., random forest), can be effectively used in predictive process monitoring for remaining time prediction in manufacturing systems (Santin Botelho et al., 2025).

7) Research Gaps

Based on the analysis of the reviewed literature and challenge distributions, several interconnected research gaps are identified. While the upward trend in publications since 2019 indicates growing momentum in applying PM across SC fields, the concentration of research within production and logistics suggests that other critical domains such as procurement, reverse logistics, and after-sales service remain underexplored. There is limited understanding of how PM techniques can be adapted to the unique data characteristics of these domains. The low frequency of real-time processing research represents a significant gap, as streaming PM techniques, online discovery algorithms, and real-time conformance checking tailored to SC contexts remain underdeveloped. The distribution of PM stages reveals that while discovery receives substantial attention, conformance checking remains comparatively underexplored, with limited research focused on validating discovered models against expected behaviors, particularly where service level agreements and regulatory requirements provide rich opportunities for analysis. Furthermore, the gap between enhancement and discovery highlights that while many studies uncover processes, fewer translate these findings into actionable improvements, indicating insufficient work on practical implementation and optimization. Limited attention to model quality assessment reveals a gap in domain-specific metrics that account for multiple organizations, geographic dispersion, and complex temporal dependencies beyond conventional measures. Governance and privacy challenges remain inadequately addressed, with limited research on multi-organizational data governance frameworks and privacy-preserving techniques for cross-organizational analysis without compromising data sovereignty. The limited research on generalization reveals a gap in understanding how PM models can be adapted across SC contexts through transfer learning and domain adaptation. A critical gap exists in the limited integration of mathematical optimization models with PM, as current approaches rarely combine exact optimization methods with event data for prescriptive analytics and decision support. Similarly, the adoption of artificial intelligence and machine learning techniques within PM remains nascent, with insufficient research on deep learning for predictive process monitoring, reinforcement learning for adaptive process optimization, and hybrid approaches that leverage both PM and machine learning capabilities. The predominance of human factors and organizational challenges reveals a gap in interdisciplinary approaches integrating organization science and change management with technical research. The distribution of tool adoption reveals that while researchers face a trade-off between accessible tools and deeply functional platforms, limited research examines how industry-grade tools can be leveraged for rigorous investigation, and programmatic approaches for flexible, reproducible analyses remain underexplored. While data quality receives attention, data collection and infrastructure remain comparatively underexplored, with limited research on event log design and data pipeline architectures. Finally, the interconnected nature of challenges reveals that isolated technical solutions dominate, with insufficient development of integrated frameworks connecting data integration, process modeling, analytics, optimization models, machine learning techniques, and scalability.

8) Conclusion and Future Research

To achieve the objective of this study, 31 articles from scientific journals related to PM in different fields of the SC were selected. The article selection process employed a combined quantitative and qualitative method for the systematic review. In each selected article, the objectives and challenges were identified, and suggestions for overcoming limitations in future studies were synthesized. The answers to the main research questions, based on the results and findings of the selected articles, were then synthesized. The search and selection of articles utilized a combination of relevant keywords across reliable scientific databases, with an effort to maximize the coverage of this contemporary field. The findings and suggestions offerred managers a pathway to improve company performance and productivity to achieve success in a competitive market. For researchers, these developments suggest several priority directions: developing supply-chain-specific quality metrics for process models, advancing transfer learning techniques that account for varying process configurations across different SC settings, and addressing the persistent under-representation of real-time processing research relative to industry demand. For practitioners, the evolution from PM to process intelligence—integrating discovery, prediction, orchestration, and automation—offers a roadmap for moving beyond diagnostic insights to operational transformation. Future research can expand upon this work by conducting further searches to explore additional dimensions of this evolving field.

References

Aalst, W., Bolt, A., & van Zelst, S. (2017). RapidProM: Mine your processes and not just your data. *arXiv preprint arXiv:1703.03740*. https://doi.org/10.48550/arXiv.1703.03740

Aghazadeh, D., & Ertogral, K. (2025). A fix and optimize method based approximate dynamic programming approach for the strategic fleet sizing and delivery planning problem. *Central European Journal of Operations Research, 33*, 91-119, https://doi.org/10.1007/s10100-024-00911-6

Aloini, D., Benevento, E., Stefanini, A., & Zerbino, P. (2020). Process fragmentation and port performance: Merging SNA and text mining. *International Journal of Information Management, 51*, 101925, https://doi.org/10.1016/j.ijinfomgt.2019.03.012

Anich, N., & Mateo-Doll, M. (2024). Manufacturing synergies in the redesign of multi-business supply chains through linear programming to meet the evolution of demand. *Central European Journal of Operations Research, 33*(4), 1251-1281. https://doi.org/10.1007/s10100-024-00918-z

Bakhshi, A., Hassannayebi, E., & Sadeghi, A. H. (2023). Optimizing sepsis care through heuristics methods in process mining: A trajectory analysis. *Healthcare Analytics, 3*, 100187, https://doi.org/10.1016/j.health.2023.100187

Berti, A., Jessen, U., Park, G., Rafiei, M., & van der Aalst, W. M. P. (2025). Analyzing interconnected processes: Using object-centric process mining to analyze procurement processes. *International Journal of Data Science and Analytics, 20*, 475-497, https://doi.org/10.1007/s41060-023-00427-3

Berti, A., Zelst, S. J. v., & Aalst, W. v. d. (2019). Process Mining for Python (PM4Py): Bridging the gap between process- and data science. *arXiv preprint arXiv:1905*. 06169, https://doi.org/10.48550/arXiv.1905.06169

Bodendorf, F., Dentler, S., & Franke, J. (2023). Digitally enabled supply chain integration through business and process analytics. *Industrial Marketing Management, 114*, 14-31, https://doi.org/10.1016/j.indmarman.2023.07.005

Celik, U., & Yurtay, Y. (2025). Improvement of assemble-to-order model processes with process mining: Dynamic analysis and hybrid approaches. *IEEE Access, 13*, 23866-23876, https://doi.org/10.1109/ACCESS.2025.3538171

Chamorro, M., & Maturana, S. (2013) Method for applying process mining to the distribution of non-alcoholic beverages. In *32nd International Conference of the Chilean Computer Science Society (SCCC)* (pp. 111-115). IEEE. https://doi.org/10.1109/SCCC.2013.26

Chiò, E., Alfieri, A., & Pastore, E. (2021). Change-point visualization and variation analysis in a simple production line: A process mining application in manufacturing. *Procedia CIRP, 99*, 573-579, https://doi.org/10.1016/j.procir.2021.03.122

Choueiri, A. C., & Portela Santos, E. A. (2021a). Discovery of path-attribute dependency in manufacturing environments: A process mining approach. *Journal of Manufacturing Systems, 61*, 54-65, https://doi.org/10.1016/j.jmsy.2021.08.005

Choueiri, A. C., & Portela Santos, E. A. (2021b). Multi-product scheduling through process mining: bridging optimization and machine process intelligence. *Journal of Intelligent Manufacturing, 32*, 1649-1667, https://doi.org/10.1007/s10845-021-01767-2

Choueiri, A. C., Sato, D. M. V., Scalabrin, E. E., & Santos, E. A. P. (2020). An extended model for remaining time prediction in manufacturing systems using process mining. *Journal of Manufacturing Systems, 56*, 188-201, https://doi.org/10.1016/j.jmsy.2020.06.003

Delgado, A., Calegari, D., Espino, C., & Ribero, N. (2025). Predictive process monitoring for collaborative business processes: concepts and application. *Discover Analytics, 3*, 5, https://doi.org/10.1007/s44257-025-00031-8

Dunzer, S., Zilker, S., Weinzierl, S., Tang, W., Dieckmann, F., Stenglein, S., Rist, J., & Matzner, M. (2025). A technology-specific process mining maturity grid for manufacturing and logistics. *International Journal of Production Research, 63*, 4431-4457, https://doi.org/10.1080/00207543.2025.2451810

Dzihni, A. S., Andreswari, R., & Hasibuan, M. A. (2019). Business process analysis and academic information system audit of helpdesk application using genetic algorithms a process mining approach. *Procedia Computer Science, 161*, 903-909, https://doi.org/10.1016/j.procs.2019.11.198

Effendi, Y. A., & Kim, M. (2025). Reliable process tracking under incomplete event logs using timed genetic-inductive process mining. *Systems, 13*, 229, https://doi.org/10.3390/systems13040229

Er, M., Arsad, N., Astuti, H. M., Kusumawardani, R. P., & Utami, R. A. (2018). Analysis of production planning in a global manufacturing company with process mining. *Journal of Enterprise Information Management, 31*, 317-337, https://doi.org/10.1108/JEIM-01-2017-0003

Eulerich, M., Huang, Q., Pawlowski, J., & Vasarhelyi, M. A. (2025). Using process mining as an assurance tool in the three-lines-model. *International Journal of Accounting Information Systems, 56*, 100731, https://doi.org/10.1016/j.accinf.2025.100731

Fairooz, T., Iftikhar, A., Tariq, Z., McClean, S., & McChesney, I. (2025) Enhancing process mining on sparse event logs: A simulation-driven academic case study. In *2025 12th International Conference on Information Technology (ICIT)*, 671-676. https://doi.org/10.1109/ICIT64950.2025.11049219

Farahani, B., & Monsefi, A. K. (2023). Smart and collaborative industrial IoT: A federated learning and data space approach. *Digital Communications and Networks*, *9*, 436–447. https://doi.org/10.1016/j.dcan.2023.01.022

Fernández-Zabalza, A., Rodríguez-Díaz, Á., Veiga, F., Suárez, A., Uralde, V., Ballesteros, T., & Alfaro, J. R. (2025). AI-driven predictive modeling of homogeneous bead geometry for WAAM processes. *The International Journal of Advanced Manufacturing Technology*. https://doi.org/10.1007/s00170-025-16061-1

Gavric, A., Bork, D., & Proper, H. (2024). Multimodal process mining. In *2024 26th International Conference on Business Informatics (CBI)* (pp. 99–108). https://doi.org/10.1109/CBI62504.2024.00021

Gavric, A., Bork, D., & Proper, H. A. (2025). Enriching business process event logs with multimodal evidence. In *The Practice of Enterprise Modeling* (pp. 175–191). Springer Nature Switzerland.

Ghag, N., Sonar, H., Sawant, R., & Bankapalli, K. (2025). Examining industry 5.0 and supply chain performance: An empirical study for managing supply chain complexity. *Production & Manufacturing Research*, *13*, Article 2501181. https://doi.org/10.1080/21693277.2025.2501181

Gianola, A., Ko, J., Maggi, F. M., Montali, M., & Winkler, S. (2025). Approximate conformance checking: Fast computation of multi-perspective, probabilistic alignments. *Information Systems*, *129*, Article 102510. https://doi.org/10.1016/j.is.2024.102510

Goossens, A., De Smedt, J., & Vanthienen, J. (2024). *Object-centric event logs: Specifications, comparative analysis and refinement*. arXiv. https://doi.org/10.48550/arXiv.2405.12709

Grant, M. J., & Booth, A. (2009). A typology of reviews: An analysis of 14 review types and associated methodologies. *Health Information and Libraries Journal*, *26*, 91–108. https://doi.org/10.1111/j.1471-1842.2009.00848.x

Grohs, M., Pfeiffer, P., & Rehse, J.-R. (2025). Proactive conformance checking: An approach for predicting deviations in business processes. *Information Systems*, *127*, Article 102461. https://doi.org/10.1016/j.is.2024.102461

Gurgen Erdogan, T., & Tarhan, A. (2018). A goal-driven evaluation method based on process mining for healthcare processes. *Applied Sciences*, *8*(6), Article 894. https://doi.org/10.3390/app8060894

Gyarmathy, A., Perényi, Á., & Mesek, M. (2025). Examining the use of Industry 4.0 technologies in e-commerce supply chains: A model of antecedents and outcomes of data-sharing platform applications. *Supply Chain Management*, *30*, 383–407. https://doi.org/10.1108/SCM-08-2024-0489

Hou, H., Chaudhry, S., Chen, Y., & Hu, M. (2017). Physical distribution, logistics, supply chain management, and the material flow theory: A historical perspective. *Information Technology and Management*, *18*, 107–117. https://doi.org/10.1007/s10799-015-0229-1

Hou, H., Kataev, M. Y., Zhang, Z., Chaudhry, S., Zhu, H., Fu, L., & Yu, M. (2015). An evolving trajectory – from PD, logistics, SCM to the theory of material flow. *Journal of Management Analytics*, *2*, 138–153. https://doi.org/10.1080/23270012.2015.1048753

Iwan, I., & Yahya, B. N. (2025). Vertical federated process mining framework for inter-organizational supply chain process discovery. *Data Technologies and Applications*, *60*, 1–22. https://doi.org/10.1108/DTA-07-2024-0761

Jans, M., van der Werf, J. M., Lybaert, N., & Vanhoof, K. (2011). A business process mining application for internal transaction fraud mitigation. *Expert Systems with Applications*, *38*, 13351–13359. https://doi.org/10.1016/j.eswa.2011.04.159

Johannssen, A., Qiu, P., Yeganeh, A., & Chukhrova, N. (2025). Explainable AI for trustworthy intelligent process monitoring. *Computers & Industrial Engineering*, *209*, Article 111407. https://doi.org/10.1016/j.cie.2025.111407

Kedem-Yemini, S. (2020). Analysis of cargo release services with process mining. *International Journal of Industrial Engineering and Operations Management*, *2*, 1–13. https://doi.org/10.46254/j.ieom.20200101

Kermani, M. A. M. A., Maghsoudi, M., & Darzi, E. (2024). Enhancing procurement performance in project-oriented organizations: A process analysis approach. *IEEE Access*, *12*, 134340–134354. https://doi.org/10.1109/ACCESS.2024.3462852

Khakpour, R., Ebrahimi, A., & Seyed-Hosseini, S.-M. (2025a). An integrated approach of zero defect manufacturing and process mining to avoid defect occurrence in production and improve sustainability. *International Journal of Lean Six Sigma*, *16*, 660–685. https://doi.org/10.1108/IJLSS-10-2023-0183

Khakpour, R., Ebrahimi, A., & Seyed-Hosseini, S.-M. (2025b). Lean process mining: Adopting process mining in lean manufacturing for dynamic process mapping and avoiding waste occurrence in real time. *International Journal of Lean Six Sigma*, *16*, 231–255. https://doi.org/10.1108/IJLSS-03-2024-0059

Khayatbashi, S., Miri, N., & Jalali, A. (2024). *Advancing object-centric process mining with multi-dimensional data operations*. arXiv. https://doi.org/10.48550/arXiv.2412.00393

Kitchenham, B., Brereton, P., Budgen, D., Turner, M., Bailey, J., & Linkman, S. (2009). Systematic literature reviews in software engineering—A systematic literature review. *Information and Software Technology*, *51*, 7–15. https://doi.org/10.1016/j.infsof.2008.09.009

Knoll, D., Reinhart, G., & Prüglmeier, M. (2019). Enabling value stream mapping for internal logistics using multidimensional process mining. *Expert Systems with Applications*, *124*, 130–142. https://doi.org/10.1016/j.eswa.2019.01.026

Kratsch, W., König, F., & Röglinger, M. (2022). Shedding light on blind spots – Developing a reference architecture to leverage video data for process mining. *Decision Support Systems*, *158*, Article 113794. https://doi.org/10.1016/j.dss.2022.113794

Kurganov, V., Dorofeev, A., Gryaznov, M., & Yakimov, M. (2021). Process mining as a means of improving the reliability of road freight transportations. *Transportation Research Procedia*, *54*, 300–308. https://doi.org/10.1016/j.trpro.2021.02.076

Kurniasih, J., Abas, Z. A., Asmai, S. A., & Wibowo, A. B. (2024). Process mining and simulation modeling in production systems: A review. *LogForum*, *20*, 429–453. https://doi.org/10.17270/J.LOG.001092

Lau, H. C. W., Ho, G. T. S., Chu, K. F., Ho, W., & Lee, C. K. M. (2009). Development of an intelligent quality management system using fuzzy association rules. *Expert Systems with Applications*, *36*, 1801–1815. https://doi.org/10.1016/j.eswa.2007.12.066

Lau, H. C. W., Ho, G. T. S., Zhao, Y., & Chung, N. S. H. (2009). Development of a process mining system for supporting knowledge discovery in a supply chain network. *International Journal of Production Economics*, *122*, 176–187. https://doi.org/10.1016/j.ijpe.2009.05.014

Lee, C. K. H., Choy, K. L., Ho, G. T. S., & Lam, C. H. Y. (2016). A slippery genetic algorithm-based process mining system for achieving better quality assurance in the garment industry. *Expert Systems with Applications*, *46*, 236–248. https://doi.org/10.1016/j.eswa.2015.10.035

Lee, S. K., Kim, B., Huh, M., Cho, S., Park, S., & Lee, D. (2013). Mining transportation logs for understanding the after-assembly block manufacturing process in the shipbuilding industry. *Expert Systems with Applications*, *40*, 83–95. https://doi.org/10.1016/j.eswa.2012.07.033

Leidner, J. L. (2022). Data to value: An 'evaluation-first' methodology for natural language projects. In *Natural Language Processing and Information Systems* (pp. 517–523). Springer.

Leimeister, J. M., Reinhard, P., Liessmann, A., Weinzierl, S., Zilker, S., Li, M., & Matzner, M. (2025). *Event log construction from multimodal data – A reference architecture for exploiting process mining in IT service management* [Manuscript in preparation].

Loacker, P., Pöchträger, S., Fikar, C., & Grenzfurtner, W. (2025). Process mining-enhanced quality management in food processing industries. *International Journal of Productivity and Performance Management*, *74*, 1326–1346. https://doi.org/10.1108/IJPPM-06-2024-0377

Lorenz, R., Senoner, J., Sihn, W., & Netland, T. (2021). Using process mining to improve productivity in make-to-stock manufacturing. *International Journal of Production Research*, *59*, 4869–4880. https://doi.org/10.1080/00207543.2021.1906460

Lugaresi, G., & Matta, A. (2023). Automated digital twin generation of manufacturing systems with complex material flows: Graph model completion. *Computers in Industry*, *151*, Article 103977. https://doi.org/10.1016/j.compind.2023.103977

Mahendrawathi, E. R., Zayin, S. O., & Pamungkas, F. J. (2017). ERP post implementation review with process mining: A case of procurement process. *Procedia Computer Science*, *124*, 216–223. https://doi.org/10.1016/j.procs.2017.12.149

Maita, A. R. C., Martins, L. C., López Paz, C. R., Rafferty, L., Hung, P. C. K., Peres, S. M., & Fantinato, M. (2018). A systematic mapping study of process mining. *Enterprise Information Systems*, *12*, 505–549. https://doi.org/10.1080/17517575.2017.1402371

Mamudu, A., Bandara, W., Wynn, M., & Leemans, S. (2025). Process mining success factors and their interrelationships. *Business & Information Systems Engineering*, *67*, 389–408. https://doi.org/10.1007/s12599-024-00860-z

May, M. C., Nestroy, C., Overbeck, L., & Lanza, G. (2024). Automated model generation framework for material flow simulations of production systems. *International Journal of Production Research*, *62*, 141–156. https://doi.org/10.1080/00207543.2023.2284833

Messal, D., Schaetter, F., Morelli, F., & Haas, F. (2025). *Case-centric and object-centric process mining: A use case for supply chain resilience management*. https://doi.org/10.7148/2025-0427

Monti, F., Mathew, J., Leotta, F., Koschmider, A., & Mecella, M. (2024). On the application of process management and process mining to Industry 4.0. *Software and Systems Modeling*, *23*, 1407–1419. https://doi.org/10.1007/s10270-024-01175-z

Moreira, G. P., Rodríguez, H. M., Talledo, O. L. M., Moreira, M. J. P., & Morales, J. J. P. (2025). Using classification and prediction algorithms to process surveys in the Altair® RapidMiner data mining software. *PRO HOMINUM*, *7*(2). https://doi.org/10.47606/ACVEN/PH0319

Mukha, T. (2025). Process mining-driven digital transformation of enterprise logistics for circular and sustainable supply-chain performance. *Intellectualization of Logistics and Supply Chain Management*, *32*, 88–99. https://doi.org/10.46783/smart-scm/2025-32-6

Napieraj, A., & Pyzik, N. (2025). Analysis of a logistics process based on the event log. *Applied Sciences*, *15*, Article 8968. https://doi.org/10.3390/app15168968

Novák, P., & Vyskočil, J. (2022). Digitalized automation engineering of Industry 4.0 production systems and their tight cooperation with digital twins. *Processes*, *10*(2), Article 404. https://doi.org/10.3390/pr10020404

Oldenburg, F., Hoberg, K., & Leopold, H. (2025). Process mining in supply chain management: State-of-the-art, use cases and research outlook. *International Journal of Production Research*, *63*, 2889–2904. https://doi.org/10.1080/00207543.2024.2412285

Oliveira, D., Gomes, J. V., Santos, P., Alves, E., Detro, S., & Pereira, C. (2025). Uncovering the potential and pitfalls of process mining in manufacturing. *Procedia CIRP*, *132*, 19–24. https://doi.org/10.1016/j.procir.2025.01.004

Pagani, R. N., Pedroso, B., dos Santos, C. B., Picinin, C. T., & Kovaleski, J. L. (2023). Methodi Ordinatio 2.0: Revisited under statistical estimation, and presenting FInder and RankIn. *Quality & Quantity*, *57*, 4563–4602. https://doi.org/10.1007/s11135-022-01562-y

Pan, Y., & Zhang, L. (2021). A BIM-data mining integrated digital twin framework for advanced project management. *Automation in Construction*, *124*, Article 103564. https://doi.org/10.1016/j.autcon.2021.103564

Park, G., Cho, M., & Lee, J. (2024). Leveraging machine learning for automatic topic discovery and forecasting of process mining research: A literature review. *Expert Systems with Applications*, *239*, Article 122435. https://doi.org/10.1016/j.eswa.2023.122435

Park, J., & Lee, B. K. (2020). Liner-dedicated manageability estimation for port operational reliability. *Reliability Engineering & System Safety*, *198*, Article 106897. https://doi.org/10.1016/j.ress.2020.106897

Park, J., Lee, D., & Zhu, J. (2014). An integrated approach for ship block manufacturing process performance evaluation: Case from a Korean shipbuilding company. *International Journal of Production Economics*, *156*, 214–222. https://doi.org/10.1016/j.ijpe.2014.06.012

Pawlak, T. P., & Potoniec, J. (2025). ProcessM: Intelligent process mining software. *SoftwareX*, *30*, Article 102079. https://doi.org/10.1016/j.softx.2025.102079

Pradhan, S., Jans, M., & Martin, N. (2025). Process mining starts here: On expertise, exchange, and the gaps between. *Process Science*, *2*. https://doi.org/10.1007/s44311-025-00032-6

Prathama, F., Yahya, B. N., Harjono, D. D., & Er, M. (2019). Trace clustering exploration for detecting sudden drift: A case study in logistic process. *Procedia Computer Science*, *161*, 1122–1130. https://doi.org/10.1016/j.procs.2019.11.224

Rabbi, F., Banik, D., Hossain, N. U. I., & Sokolov, A. (2024). Using process mining algorithms for process improvement in healthcare. *Healthcare Analytics*, *5*, Article 100305. https://doi.org/10.1016/j.health.2024.100305

Rafiei, M., Pourbafrani, M., & van der Aalst, W. M. P. (2025). Federated conformance checking. *Information Systems*, *131*, Article 102525. https://doi.org/10.1016/j.is.2025.102525

Ramires, F., & Sampaio, P. (2022). Process mining and lean six sigma: A novel approach to analyze the supply chain quality of a hospital. *International Journal of Lean Six Sigma*, *13*, 594–621. https://doi.org/10.1108/IJLSS-12-2020-0226

Reiter, H., Edinger, J., Kabierski, M., Koschmider, A., Landsiedel, O., Lepsien, A., Lu, X., Marrella, A., Serral, E., Schult, S., Tschorsch, F., Weidlich, M., & Hasselbring, W. (2025). *ContinuumConductor: Decentralized Process Mining on the Edge-Cloud Continuum*. arXiv. https://doi.org/10.48550/arXiv.2512.07280

Rudnitckaia, J., Venkatachalam, H. S., Essmann, R., Hruška, T., & Colombo, A. W. (2022). Screening process mining and value stream techniques on industrial manufacturing processes: Process modelling and bottleneck analysis. *IEEE Access*, *10*, 24203–24214. https://doi.org/10.1109/ACCESS.2022.3152211

Ruschel, E., Rocha Loures, E. d. F., & Santos, E. A. P. (2021). Performance analysis and time prediction in manufacturing systems. *Computers & Industrial Engineering*, *151*, Article 106972. https://doi.org/10.1016/j.cie.2020.106972

Sánchez, M., Exposito, E., & Aguilar, J. (2020). Implementing self-* autonomic properties in self-coordinated manufacturing processes for the Industry 4.0 context. *Computers in Industry*, *121*, Article 103247. https://doi.org/10.1016/j.compind.2020.103247

Santin Botelho, J. G., Portela Santos, E. A., Choueiri, A. C., & Pécora Junior, J. E. (2025). Remaining time prediction in manufacturing systems: An approach based on ML and process mining. *Procedia CIRP*, *132*, 165–170. https://doi.org/10.1016/j.procir.2025.01.028

Shiying, N., Xiwen, B., Yuchen, L., Pang, Z., & Li, L. (2022). Blockchain-based traceability system for supply chain: Potentials, gaps, applicability and adoption game. *Enterprise Information Systems*, *16*, 1908–1937. https://doi.org/10.1080/17517575.2022.2086021

Stefanovic, D., Dakic, D., Stevanov, B., & Lolic, T. (2020). Process mining in manufacturing: Goals, techniques and applications. In *International Federation for Information Processing* (pp. 54–62). Springer. https://doi.org/10.1007/978-3-030-57993-7_7

Su, X., Liu, C., Lu, F., Cheng, L., Zeng, Q., & Zhang, S. (2025). EdgeIM: An efficient edge-based process model discovery technique. In *2025 IEEE International Conference on Web Services (ICWS)* (pp. 1–7). IEEE. https://doi.org/10.1109/ICWS67624.2025.00057

Sungkono, K. R., Sarno, R., Onggo, B. S., & Haykal, M. F. (2023). Enhancing model quality and scalability for mining business processes with invisible tasks in non-free choice. *Journal of King Saud University – Computer and Information Sciences*, *35*, Article 101741. https://doi.org/10.1016/j.jksuci.2023.101741

Thiede, M., Fuerstenau, D., & Barquet, A. (2018). How is process mining technology used by organizations? A systematic literature review of empirical studies. *Business Process Management Journal*, *24*, 900–922. https://doi.org/10.1108/BPMJ-06-2017-0148

Tran, T.-A., Ruppert, T., & Abonyi, J. (2021). Indoor positioning systems can revolutionise digital lean. *Applied Sciences*, *11*, Article 5291. https://doi.org/10.3390/app11115291

Tridalestari, F. A., Mustafid, & Jie, F. (2023). Consumer behavior analysis on sales process model using process discovery algorithm for the omnichannel distribution system. *IEEE Access*, *11*, 42619–42630. https://doi.org/10.1109/ACCESS.2023.3271394

van den Elzen, S., Jans, M., Martin, N., Pieters, F., Tominski, C., Villa-Uriol, M.-C., & van Zelst, S. J. (2025). Towards multi-faceted visual process analytics. *Information Systems*, *133*, Article 102560. https://doi.org/10.1016/j.is.2025.102560

van der Aalst, W. (2016). Data science in action. In *Process mining: Data science in action* (pp. 3–23). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-49851-4_1

van der Aalst, W. M. P., Reijers, H. A., & Maruster, L. (2024). Process mining beyond workflows. *Computers in Industry*, *161*, Article 104126. https://doi.org/10.1016/j.compind.2024.104126

Wang, Q., & Thelkar, A. R. (2024). A novel stackelberg game-theoretic optimization model for interaction between two closed-loop supply chains with a queueing approach. *Journal of Engineering Research*. Advance online publication. https://doi.org/10.1016/j.jer.2024.01.021

Wang, Y., Caron, F., Vanthienen, J., Huang, L., & Guo, Y. (2014). Acquiring logistics process intelligence: Methodology and an application for a Chinese bulk port. *Expert Systems with Applications*, *41*, 195–209. https://doi.org/10.1016/j.eswa.2013.07.021

Wangelik, F., Rafiei, M., Pourbafrani, M., & van der Aalst, W. M. P. (2025). Releasing differentially private event logs using generative models. *Data & Knowledge Engineering*, *159*, Article 102450. https://doi.org/10.1016/j.datak.2025.102450

Wikusna, W., Mustafid, & Jie, F. (2024). Performance measurement in a custom production process model using the process mining approach: A systematic literature review. *IEEE Access*, *12*, 173552–173556. https://doi.org/10.1109/ACCESS.2024.3498433

Yang, Y., Wu, Z., Chu, Y., Chen, Z., Xu, Z., & Wen, Q. (2024). *Intelligent cross-organizational process mining: A survey and new perspectives*. arXiv. https://doi.org/10.48550/arXiv.2407.11280

Yari Eili, M., & Rezaeenour, J. (2022). A survey on recommendation in process mining. *Concurrency and Computation: Practice and Experience*, *34*, Article e7304. https://doi.org/10.1002/cpe.7304

Yari Eili, M., & Rezaeenour, J. (2023). An approach based on process mining to assess the quarantine strategies' effect in reducing the COVID-19 spread. *Library Hi Tech*, *41*, 25–41. https://doi.org/10.1108/LHT-01-2022-0062

Yari Eili, M., Rezaeenour, J., & Fani Sani, M. (2021). *A systematic literature review on process-aware recommender systems*. arXiv. https://doi.org/10.48550/arXiv.2103.16654

Zayed, E., & Hatem, M. (2026). Blockchain, transparency and trust in supply chains: Insights from professionals' perceptions. *Journal of Transport and Supply Chain Management*, *20*. https://doi.org/10.4102/jtscm.v20i0.1255

Zerbino, P., Aloini, D., Dulmin, R., & Mininno, V. (2018). Process-mining-enabled audit of information systems: Methodology and an application. *Expert Systems with Applications*, *110*, 80–92. https://doi.org/10.1016/j.eswa.2018.05.030

Zerbino, P., Aloini, D., Dulmin, R., & Mininno, V. (2019). Towards analytics-enabled efficiency improvements in maritime transportation: A case study in a Mediterranean port. *Sustainability*, *11*, Article 4473. https://doi.org/10.3390/su11164473