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REVIEW

Simulation and process mining: review and outlook

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Abstract

Modeling and simulation of business processes have consistently played a pivotal role in science and industry, increasingly benefiting from process mining algorithms that enable the generation of models and parameter extractions. This paper presents a systematic literature review that explores the integration of simulation with process mining techniques, offering a comprehensive overview of contemporary methodologies, applications, and challenges within this interdisciplinary field. Special emphasis is placed on how simulation approaches are employed and enhanced through process mining, revealing opportunities for improved accuracy, scalability, and applicability in complex process environments. First, network analysis enables the identification of underlying patterns and relationships within the research landscape, revealing insights that may not be captured by conventional review methods. Second, a structured literature analysis provides a comprehensive framework that delineates key modeling tasks, categorizes application domains, tools, and validation strategies, and identifies gaps and opportunities at the intersection of simulation and process mining, discussing future advancements in the field.

Keywords Process mining · Simulation · Systematic literature review

1 Introduction

Recent technological developments and the availability of big data present organizations with opportunities, but also challenges in managing the increasing complexity of processes or the high volumes of unstructured data. Traditional methodologies can be combined with advanced techniques, such as simulation, data mining, and process analysis [1, 2]. Managing a wide range of business processes, such as procure-to-pay and order-to-cash, is essential for efficiently delivering products or services to customers [3]. When changes in a process need to be made to improve its performance or to adapt it to contextual changes, experimenting with the real-life process is often not feasible, given the costs it would entail. In such contexts, simulation can play a key role in supporting decision-making.

Business process simulation (BPS) is a widely used technique that mimics business process behavior using a computerized simulation model. The BPS model encodes how the process behaves such that dynamic objects called entities (e.g., orders in an order handling process) can flow through the process to generate a variety of simulated process performance metrics such as the average waiting time or resource utilizations [4]. In this way, the BPS model supports the process analyst in assessing the impact of various factors, such as changes in environmental factors or internal process modifications, on the performance of the real-world process. By allowing users to answer "what-if" questions, simulation enables organizations to gain insights into the impact of process changes before actually implementing them [5, 6].

While BPS is widely studied in the operations research domain [5, 7], the importance and the potential benefits of BPS have been acknowledged since the early developments of the Business Process Management (BPM) field. Recent years have seen a surge in interest in more sophisticated simulation models for processes in various domains, ranging from

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administrative processes [8] to manufacturing [9] or healthcare [10]. Modern organizations must be able to quickly adapt their processes and operations to gain and maintain a competitive advantage in today's fast-paced, dynamic environment, and BPS provides a crucial asset for making such decisions.

Building a BPS model that mimics the process behavior accurately requires in-depth knowledge about how the process is executed in reality. This can relate, for instance, to the activities in the process, their order, their duration, the resources involved and the decision logic used when choices need to be made [4]. Traditionally, this expert knowledge was gathered manually using, e.g., interviews or observations. More recently, data stored in organisations' information systems is also leveraged during BPS model construction as it enables using data-driven approaches to model at least some elements. In particular, previous studies advocated using *Process Mining* algorithms to support the development of BPS models [4, 11]. Process mining is a steadily growing research field aimed at discovering, analyzing and improving business processes starting from an *event log* tracking past process executions [12]. As such, process mining techniques generate evidence-based insights into how the process is actually performed, which are needed to generate accurate BPS models [4, 11].

Most existing studies that use process mining to develop BPS models focus on (i) proposing a novel method to support a (subset of) simulation modeling task(s) using process mining or (ii) applying (a combination of) existing process mining methods within a specific case study in which a simulation model is created. While both streams of research have attracted increased attention in recent years, it remains unclear how comprehensive the process mining support for BPS model development currently is and how this emerging research topic should evolve toward the future. This knowledge gap arises from the absence of a structured overview of previous research efforts as a basis for discerning promising areas for future research.

In this work, our aim is to fill this gap by performing a systematic review of the literature to obtain a structured overview of research on the use of process mining in the context of BPS. Some recent work has addressed the intersection of process mining and simulation from more specialized perspectives, focusing either on specific application domains, such as healthcare [13, 14], or on particular simulation paradigms, such as agent-based modeling [15, 16]. In contrast, our review adopts a broader and more inclusive perspective. We systematically consider all three primary simulation paradigms, i.e. Discrete-Event Simulation (DES), System Dynamics (SD), and Agent-Based Modeling (ABM), rather than concentrating on a single modeling approach. Furthermore, we do not restrict our analysis to a specific application domain; instead, we examine contributions across domains from a business process perspective, focusing specifically on simulation models that are explicitly grounded in process mining techniques, as detailed in the following sections. In particular, we aim to understand how research on the integration of process mining and simulation has evolved, which topics have received the greatest attention, which research groups have been most active, and which contributions have played a central role in shaping the field. To this end, we formulate the following research question: *"(RQ1) What are the main research themes, collaboration patterns, and influential contributions in the intersection of process mining and simulation?"*

We subsequently investigate the methodological and application-oriented aspects of the literature through the following research question: *"(RQ2) What are the current methodologies, applications, and challenges in integrating process mining techniques with business process simulation?"*.

By answering this question, we can gather relevant insights into the current state of research and practice in the interplay of process mining and simulation. We are especially interested in determining current trends, practical implications for research and practice, gaps, and opportunities for further improvements.

Our analysis resulted in multi-fold contributions. First, to address RQ1, we employ network analysis techniques and conduct a focused examination of the most recent years of research. Second, to address RQ2, within our SLR we provide a framework encompassing the most important BPS modeling tasks, updating the ones from state-of-the-art [4] to account for recent developments on topics previously neglected (e.g., resource behaviors). We map each identified task to the process mining techniques used in the literature. Third, we categorize application domains, tools, and validation strategies found in the literature to infer evidence-based insights into how these techniques have been used in the industry and to extract good practices and common pitfalls. Finally, we reflect upon the analyzed studies to delineate research directions for future work on this highly relevant research topic.

The remainder of the paper is structured as follows. Section 2 positions the present study within the existing literature. Section 3 outlines the methodology of the systematic literature review, which encompasses an overview of the research domain through network analysis and a structured analysis of article content. Section 4 describes an overview of network analysis results. Section 5 presents structured literature search, while Sect. 6 discusses the results. Section 7 concludes the paper.

2 Background and related reviews

This section examines recent contributions reviewing the integration of process mining and simulation, with the aim of positioning the present survey within the current state of the art. In particular, four similar works have explored the topic from domain-specific perspectives (e.g., healthcare or manufacturing), or from paradigm-focused viewpoints (e.g., agent-based modeling): Bemthuis (2025) [15], Salas (2024) [13] Schmolke (2024) [14], and Kurniasih (2024) [17].

To summarize the main differences (see Table 1), we compare the surveys based on three criteria: (i) *temporal coverage*, reflecting the historical breadth of the literature examined; (ii) *domain focus*, distinguishing cross-domain from sector-specific reviews; and (iii) *predominant simulation paradigm focus*, identifying whether a review is single-paradigm centered or adopts a cross-paradigm perspective. Most studies cover literature published between the early 2000s and 2023–2024, reflecting the emergence of process mining in the mid-2000s and its progressive integration with simulation techniques. Consistently, our SLR spans the full historical development of the field, from its early methodological foundations to the most recent advances in automated and data-driven simulation modeling.

In terms of domain focus, three reviews are domain-specific: two concentrate on healthcare applications, while one targets manufacturing and production systems. In contrast, Bemthuis (2025) and our SLR adopt a cross-domain perspective, considering contributions across multiple sectors. This broader scope enables a more comprehensive understanding of methodological trends beyond sector-specific implementations.

Finally, most reviews are single-paradigm focused, predominantly centered on discrete-event simulation (DES). The Bemthuis review differs by concentrating specifically on agent-based modeling (ABM). Our SLR is the only contribution explicitly adopting a cross-paradigm perspective, comparatively addressing DES, ABM, and SD. This distinction underscores the broader methodological scope of the present survey, which treats simulation paradigms as an explicit analytical dimension rather than as an implicit modeling assumption.

Additionally, a recent study [18] addresses simulation within the broader architectural context of digital twins. Although it can be considered a systematic review, it does not focus on the methodological integration between process mining and simulation as a primary analytical dimension.

Similarly, [19] provides an early general overview of research efforts combining process mining and simulation. Due to its earlier publication date (2018), which predates recent methodological and technological advances in automated and data-driven simulation modeling, it cannot be meaningfully compared with the present survey. Nevertheless, this work underscores the longstanding research interest in these topics.

3 Methodology

This Section outlines the SLR methodology, as represented by the pipeline in Fig. 1. First, the initial *search stage* includes the steps for collecting the documents of interest from the reference databases to construct the relevant body of literature. Once queries are made on the datasets, the records are checked to eliminate duplicates/errors ("paper identification"). Then, a "title and abstract reading" phase has been performed, to select articles of interest. Finally, the "full-text article reading" led to the final set of papers on which the *analysis stage* has been performed. The *analysis stage* combines an "exploratory network analysis" with a structured review grounded in systematic "paper coding" of the final set of selected studies. The following subsections examine both stages in more detail.[1]

3.1 Search stage: paper collection and selection

The structured process for collecting and selecting papers is summarized in a standard pipeline, as shown in Fig. 2, following the PRISMA methodology [20].

Paper identification Four scientific databases have been considered: Scopus, Web of Science (WoS), IEEE Xplore, ACM Digital Library. After exploratory scoping searches, the search queries used are presented in Appendix 8.

We collected papers in the range of the last 20 years, i.e., the period from 2004 to 2025 (including articles published online as articles in press). This period is consistent with the emergence and spread of the process mining discipline. In total, 1,013 papers were identified. Most of the papers come from Scopus (602), then from WoS (293), IEEE (105).

Screening To select the relevant papers from the results of the literature search queries, a three-stage approach has been used.

Firstly, *duplicates* were removed as some papers were part of the search results of multiple databases. After duplicate removal, 702 papers remained.

Secondly, *a title and abstract reading* were performed. During this screening, the inclusion criterion was to verify that the main focus of the paper is the use of process mining within a simulation context. To better circumscribe the scope of interest, we have applied a set of exclusion criteria, as outlined in Table 2. The exclusion criteria are varied and cover several factors typical of a literature review (e.g., lack

[1] SLR process files, code, images are publicly available in the following repository: https://t.ly/VIlGc

Table 1 Comparison of recent survey papers on the integration of process mining and simulation

Survey paper	Temporal coverage	Domain focus	Simulation paradigm
Bemthuis (2025)	Up to July 2022	Cross-domain	ABM
Schmolke (2024)	Up to 2023	Healthcare	DES
Salas (2024)	2009–2022	Healthcare	DES
Kurniasih (2024)	2020–2024	Manufacturing	DES
Present SLR	2004–2025	Cross-domain	DES-ABM-SD

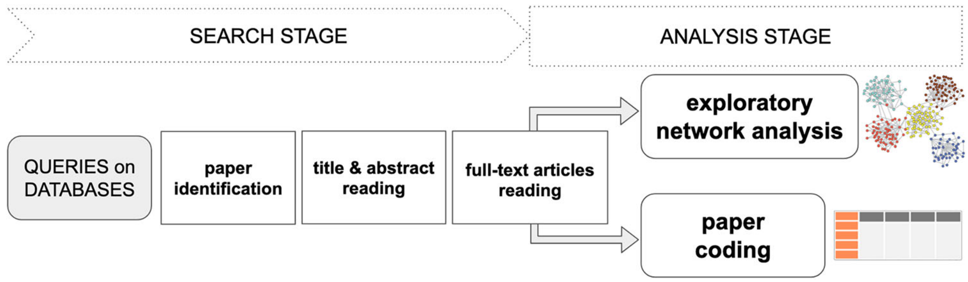


Fig. 1 Pipeline of the search literature review

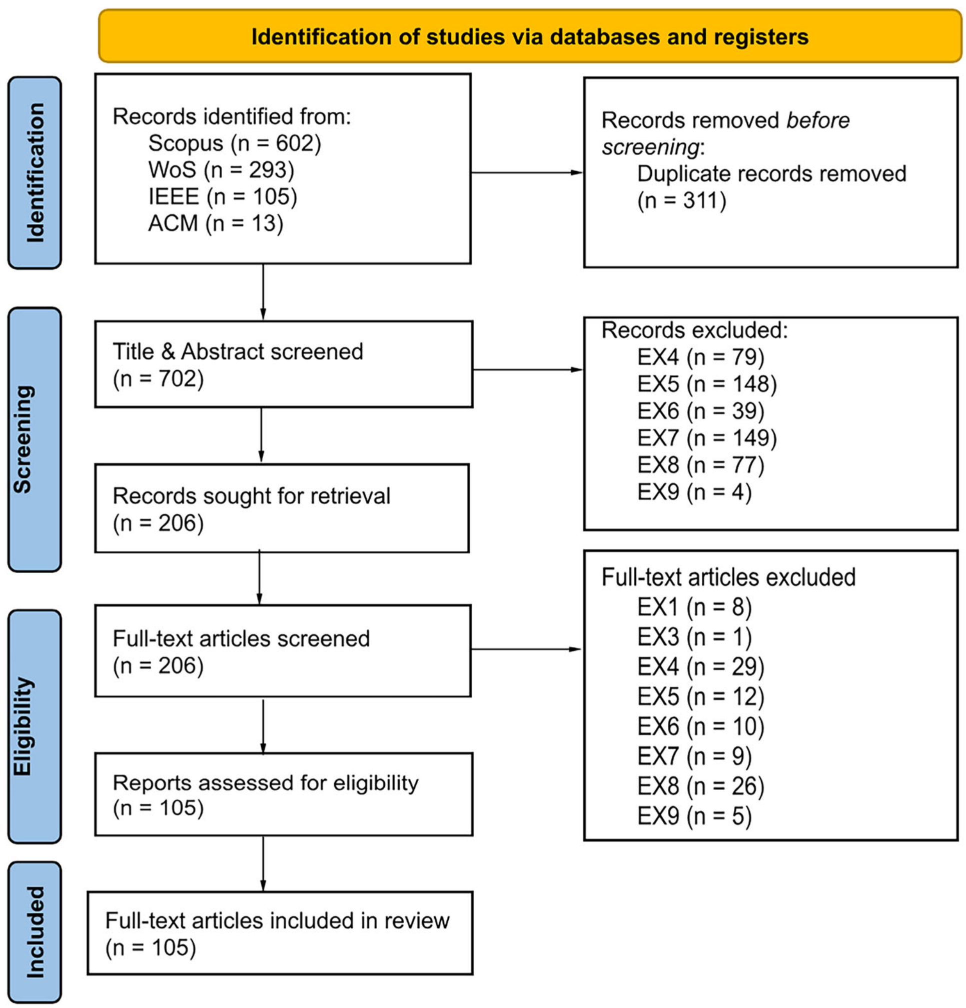


Fig. 2 Detailed view of the *search stage* according to the PRISMA methodology

of full paper, focus on process mining while simulation has been used only for validation, etc.). We also excluded papers that make a contribution regarding the use of process mining in the context of simulation at a conceptual level, e.g. no executable method is provided.

A conservative approach has been followed: when the title and abstract provided insufficient information to make a decision about a paper, the paper was included in the next paper selection stage. After title and abstract screening, 206 papers were retained.

Eligibility The careful examination of the 206 articles previously selected led to a further refinement of the sample of articles of interest. Finally, 105 articles were included in the final stage of our survey, and thus subject to a thorough structured analysis, while 101 cases were excluded with different motivations. We present an overview of the excluded cases, and then focus on the dimensions of the structured survey for *included* papers in the following Section.

Overview of excluded papers There are three prevailing reasons for the exclusion of articles at this stage. First, several papers focused mainly on simulation (and, e.g., generates an event log as an output), without process mining being a core topic (26 papers). Second, a large group of papers were particular cases of publications, e.g., extended abstracts, research plans, demo papers, or keynote speeches (29). Another relevant exclusion criterion concerned works that do not present any executable methods, but simply adopt process mining techniques in the context of simulation at the conceptual level (12). In other minor cases, the excluded papers had a focus on process mining, while using simulated data only for demonstration or evaluation purposes (10), without simulation being a core topic (9). In other cases, the core topic of the paper was neither process mining, nor simulation (12). Finally, some articles were discarded because the article had not been peer-reviewed or the full text was not available (8), as well as an extended version of the same article was already included in the document set (5).

3.2 Analysis stage: examination of the articles

The final paper set has been analyzed in a twofold manner, i.e. (i) by conducting an exploratory network analysis and (ii) by coding the papers based on a set of variables of interest. We first address RQ1 through exploratory network analysis, which complements the structured paper review by providing an overview of the field. In particular, network-based techniques support SLRs by highlighting dominant research topics, identifying active research communities, and detecting influential contributions within the corpus of publications [21–23]. Subsequently, to address RQ2, we conduct a structured review based on the coding and in-depth examination of the selected studies. At all stages of the review process, records were screened independently by two members of the author team. In case of disagreement, a third reviewer was involved and, if necessary, a discussion was held to reach consensus. The inter-annotator agreement for the three annotator pairs was 75%, 80%, and 85%, respectively. In particular, Cohen's kappa values of 0.53, 0.59, and 0.63 clearly indicate moderate to substantial agreement. The discussion of ambiguous cases always led to consensus on all papers.

3.2.1 Analysis stage: exploratory network analysis

Network analysis provides a powerful tool for automatically extracting insights on a corpus by revealing underlying patterns and relationships among interconnected elements [24]. Before describing the analyses in detail, we present some general concepts of interest that will be adopted in this paper. Networks are structures that connect vertices by means of edges, the weight of which may indicate the extent or strength of the connection. Networks can be undirected, if the edges have no direction, or directed in case the direction has meaning. The connections of each vertex can be counted (degree). In the case of directed networks, it is also possible to distinguish between edges entering (in-degree) or leaving the vertex (out-degree).

In this paper, network analysis is applied to explore the final paper set. In particular, three commonly used bibliometric networks are considered: a co-author network, a citation network, and a co-occurrence network [25]. Three main types of research can take place: calculating general measures of the network (e.g., the *density* measure indicating the fraction of existing edges out of the total); calculating particular measures at the level of vertices or edges (e.g., the *betweenness centrality* measure indicates which vertex is more central than other vertices and thus its role within the network); and applying algorithms to the network to automatically extract information (e.g., *clustering* algorithms to identify the most connected groups or areas). We used the tool Gephi[2] to investigate the most common network measures, while to identify clusters we adopt the well-known community detection method *Louvain modularity* [26].

Finally, a preliminary filtering step may be applied to remove less significant vertices or edges in order to focus on the most informative part of the network. This may involve, for example, excluding vertices with low degree or edges with low weight. Since network structures can vary substantially depending on corpus size, density, and research domain, filtering decisions were guided by inspection of the network structure and expert interpretation in order to preserve structural meaning while improving interpretability [25]. Nevertheless, a sensitivity analysis is conducted by varying the filtering thresholds and introducing small per-

[2] https://gephi.org/

Table 2 Exclusion criteria adopted in the review stage

Acronym	Exclusion criteria
EX1	The full-text of the paper is not available
EX2	The paper is not written in English
EX3	The paper has not been peer reviewed
EX4	The paper is a review paper, one-pager, abstract, extended abstract, editorial, research plan, project proposal, tutorial, presentation, poster, keynote speech, demo, or a conceptual paper
EX5	The core topic of the paper is neither process mining, nor simulation
EX6	The paper has a focus on process mining and uses simulated data for demonstration/evaluation purposes
EX7	The paper focuses on process mining (and, e.g., mentions simulation), without simulation being a core topic
EX8	The paper focuses on simulation (and, e.g., generates an event log as an output), without process mining being a core topic
EX9	An extended version of the core contribution is included in the paper set

turbations to the network, showing that the main clusters identified by modularity remain stable across these settings.

The following paragraphs introduce the three types of analysis.

Co-occurrence network

This network consists of the terms included in the abstracts of the final paper set as vertices, while edges connect two terms if they appear together in the same sentence. An analysis of the most used groups of terms provides an overview of the most related topics, with the degree of the vertices and the weight of the edges indicating their significance.

We introduce the steps for constructing this network. As a pre-processing phase, we apply *stemming* which simplifies and standardizes language. This allows us to group terms with similar root forms, which enhance the quality and the significance of the results. Second, we remove both the keywords used in the search queries and stop words, i.e., commonly used words in a language, which carry very little helpful information. Third, after identifying *part-of-speech* tagging, we maintain nouns, adjectives, and verbs. Finally, compound nouns and multi-word concepts have been “merged" into single terms by using a hyphen (e.g. ‘conformance checking’ becomes ‘conformance_checking’, ‘business process’ becomes ‘business_process’). Once the network is constructed, we verify whether it exhibits the expected structural properties. In particular, we analyze the degree distribution to check for a long-tailed pattern, where a small number of vertices act as hubs while most have few connections. Typically, this kind of network exhibits the so-called *small-world* property, i.e., where vertices have a small number of connections to reach each other (*average shortest path length*) and a tendency of vertices to cluster together (*high clustering coefficient*).

Co-authors network The network of co-authors consists of an undirected network in which article authors are vertices connected to each other if they appear as co-authors of the same article. This kind of network allows for an effective representation from different perspectives. First, all active collaborations among researchers can be represented. Second, the most cohesive groups of researchers collaborating in the target area can be clearly highlighted.

Citation network This network is based on the articles as vertices. Edges represent the connections from an article to the respective references. In the corresponding directed network we can detect most cited papers by their *in-degree* (InDeg). We can also exploit the *betweenness centrality* (BetwC) measure to identify the articles that play a crucial role in maintaining connectivity within the network, as in the case of an article acting as a bridge between different groups of articles.

3.2.2 Analysis stage: paper coding

In order to present a structured overview of the final paper set, the papers were coded according to several variables of interest providing a broad overview of the focus of existing research. For these variables of interest, as will be outlined below, a coding sheet was developed that described each variable and (if applicable) the potential values it could take. Each paper has been independently coded by two members of the research team. The agreement between the assigned codes was assessed and, in case of disagreement, a discussion took place to reach consensus.

The variables of interest that were coded aimed at providing a broad overview of the focus of existing research on the use of process mining in a BPS context. They were deliberately selected to complement each other. Four distinct overarching groups of variables can be distinguished. Firstly, the *paper focus* provides a general perspective on the focus of the paper, reflecting both the BPS angle in terms of the type of simulation and goal of the simulation analysis, as well as the purpose for which process mining is used. Secondly, the *tooling* used is considered, once again considering both the BPS and process mining angle. Thirdly, we identify the *data* that is used for process mining purposes, either synthetic and/or real-life data, and how the BPS model is *validated*. Finally, the *BPS modeling tasks* that were considered in a paper are identified, as well as the approach followed to model them. This enables the retrieval of insights into the BPS modeling tasks for which process mining is used, either by itself or in combination with domain knowledge. For each of these overarching groups, the specific variables that were coded are outlined below.

Paper focus The first group of variables that were coded contains five distinct variables providing a general perspective on the paper's focus. Firstly, the *general purpose for which process mining is used in the paper* was determined, which could take either one of the following three values: (i) generating an executable simulation model, either partially or fully retrieved from an event log, (ii) assessing the validity of a simulation model, or (iii) providing data-driven support for (one or more) specific simulation modeling tasks, without being integrated into an executable simulation model. Secondly, the *type of simulation* was recorded, which could refer to DES, ABM, SD, or combinations thereof. Thirdly, the *degree of automation* expressed whether the simulation model was created either in a fully automated or semi-automated way (where process mining was used to support specific aspects). Fourthly, the *goal of the simulation analysis* is retrieved, which can involve comparing scenarios or optimizing a particular component of a business process. The list of potential simulation analysis goals grew inductively while coding: each time a new goal was discovered, a shared list was appended that was available to all members of the research team. Finally, it is determined whether the paper focuses on a particular *industry* and, if so, on which industry. Similar to the goal of the simulation analysis, the list of industries inductively grew while coding.

Tooling The second group of variables of interest related to tooling. In particular, we extracted two types of tools from each paper: the *simulation tool* used to develop the BPS model and the *process mining tool* used to retrieve relevant insights from event logs from each paper. Both lists of unique tools grew inductively while coding progressed.

Used data and validation The third group of variables that were coded related to the data used for process mining purposes and how the obtained BPS model was validated. Regarding the *used data* for process mining, a distinction is made between synthetic and real-life data. While synthetic data provides a controlled environment to test, e.g., whether a process mining approach can retrieve the ground truth used to generate the synthetic data, it typically cannot capture the full complexity of real-life process behavior. Applying a process mining method on real-life data enables assessing the insights it can generate in such real-life contexts. Besides coding whether synthetic data, real-life data, or both were used, we also recorded the public or private character of the used data.

With respect to the *validation of the simulation model*, it was first determined whether a validation was reported. If so, it was further discerned whether a validation was performed using quantitative metrics and/or by discussing the model or its results with domain experts.

BPS modeling tasks A final group of variables relates to the *BPS modeling tasks* considered in the papers, i.e., elements that need to be specified when building a simulation model such as the entity arrival rate and activity durations. We considered the list of simulation modeling tasks proposed by Martin et al. [4] as a starting point for coding. However, if a modeling task was identified in a paper that did not occur on the initial list, this modeling task was appended. For each of the reported simulation modeling tasks, the *modeling approach* was recorded, which could be process mining, domain knowledge, a combination of both, or unknown, where the latter expresses that it is not reported how a modeling task has been performed. Finally, for modeling tasks for which process mining has been used, the specific *process mining algorithm* that has been leveraged was extracted to assess whether some algorithms are more frequently used than others. The list of process mining algorithms grew inductively as papers were coded.

4 Exploratory network analysis of the literature

In the following, we present the most relevant insights derived from the three networks examined in the *exploratory network analysis* of the 105 articles included in our survey.[3]

4.1 Emerging topics identified through co-occurrence networks

The co-occurrence network of stems obtained from the sentences of the abstracts of the selected papers has the characteristics of a typical complex network, with a high clustering coefficient (0.75) and a degree distribution that exhibit a long tail. As the average shortest path is relatively short (2.7, meaning that from one vertex you can reach all the

[3] We performed a sensitivity analysis by varying the minimum degree threshold (2–4) and the upper frequency cutoff (e.g., top 5–10% most frequent terms). Additionally, random perturbations were applied by removing 5% of nodes or 10% of edges. The number of clusters remained stable (5–6), and the main thematic structure was preserved. Only minor variations were observed in peripheral nodes. These results confirm the robustness of the identified clusters.

others in 3 connections on average), the network has a small-world property [27]. Once verified that the network matches the characteristics of similar networks of co-occurring terms, we further focus on the main component (in fact, few pairs of terms appear isolated in the network). Furthermore, after a manual inspection we arrange the network in a way that makes it more readable and useful, filtering out the least frequent vertices, i.e. the vertices having a degree lower than a threshold of 3. Moreover, we also removed terms that were too frequent (degree over 32) as they are not meaningful (e.g., model, data, process). Finally, we obtain clusters of stems by computing Louvain modularity. The resulting network describes the relevant concepts emerging from our abstract selection, as in Fig. 3.

We have automatically identified the following six clusters, which appear to be significant with respect to the main themes of our survey:

- *Resource and time management*. This group revolves around an integrated approach to effectively manage and evaluate resources, including time, availability, and workload. This involves assessing resource allocation, considering calendars, displaying probabilistic outcomes, managing distribution, capacity, cost, and resource pools to ensure efficient utilization and effective planning.
- *Process Modeling and Data-Driven Approach*. This group of stems refers to methods and approaches for modeling real-life systems and processes. This may combine data-driven techniques, historical knowledge, and simulation for representing novel scenarios, by exploiting events with timestamps, and incorporating various inputs for an effective and informed representation.
- *Business Process Management*. This set of stems refers to topics related to information systems and business process management, for improving activities, performance, and the management of business processes. This includes identification, improvement, execution, action, process simulation, future, forecast, scenario. Such terms refer on systems for predicting future scenarios, executing actions, organizing workflows, maintaining detailed logs, simulating business processes.
- *Validation operations and evaluation of results*. This group refers to terms concerning the assessment, validation, development, and maintenance of outcomes, operations, and results. This involves analyzing data, ensuring adequacy, and addressing relevant objects in a systematic manner.
- *Healthcare Systems*. This group of stems clearly refers to healthcare topics, by including the concepts of hospital, healthcare, medicine, patient. This set refers to decision support concepts in the healthcare domain, focusing, for example, on clinical pathways and care management.
- *Systems, Behavior, and Industrial Optimization*. This group includes articles on industrial topics such as optimisation, digital twinning technologies, and efficient management systems, i.e. production, automation, workflow, system, behavior.

4.2 Research collaborations through co-authorship networks

Through a co-author network we can obtain an overview of the distribution of the authors, as well as identify the most important active collaborations. First of all, we notice how the community emerging from our final paper set is quite large, involving 261 individual authors (vertices of the network), with 509 collaborations (edges). The network *density* is very low (0.015), indicating a sparse network. The network topology[4] identifies the existence of several groups (53 connected components), most of them small. This value suggests the presence of several relatively autonomous research groups, characterized by strong internal collaborations, limited cross-group connections, and the absence of a single dominant cluster encompassing the entire community.

The most collaborative pair of authors is Van der Aalst and Pourbafrani (edge weight of 8), while the authors with the highest number of collaborations are Marlon Dumas and Vincent Augusto (degree of 19). There are four large groups of researchers, whose authors with the highest degree are: Dumas (in a cluster of 21 authors), Augusto (20 authors), Meneghello (15 authors), Van der Aalst (13 authors). Most small groups involve several different sets of authors, e.g., researchers belonging to the same university.[5] This analysis suggests that there is great heterogeneity, with several scattered collaborations and only a few more cohesive and larger groups of collaboration networks.

4.3 Influential studies in the citation network

Analysis of the direct citation network highlights the most frequently cited and structurally prominent contributions within the 105 selected articles, supporting the identification of studies that play a relevant role within the body of literature considered in our survey. As mentioned in Sect. 3.2.1, the articles with the highest in-degree are the most cited ones, while the centrality measure of the vertices identifies the research papers which act as intermediaries between different groups and communities[6]

[4] The co-authorship networks are publicly available in the online repository at: https://t.ly/als9W

[5] This results appear from a more fine-grained view in the network of coauthors having more than 2 articles in common (see the repository)

[6] The citation network is publicly available in the online repository at: https://t.ly/mz6TP.

Fig. 3 Co-occurrence of terms in abstracts of final set of 105 papers

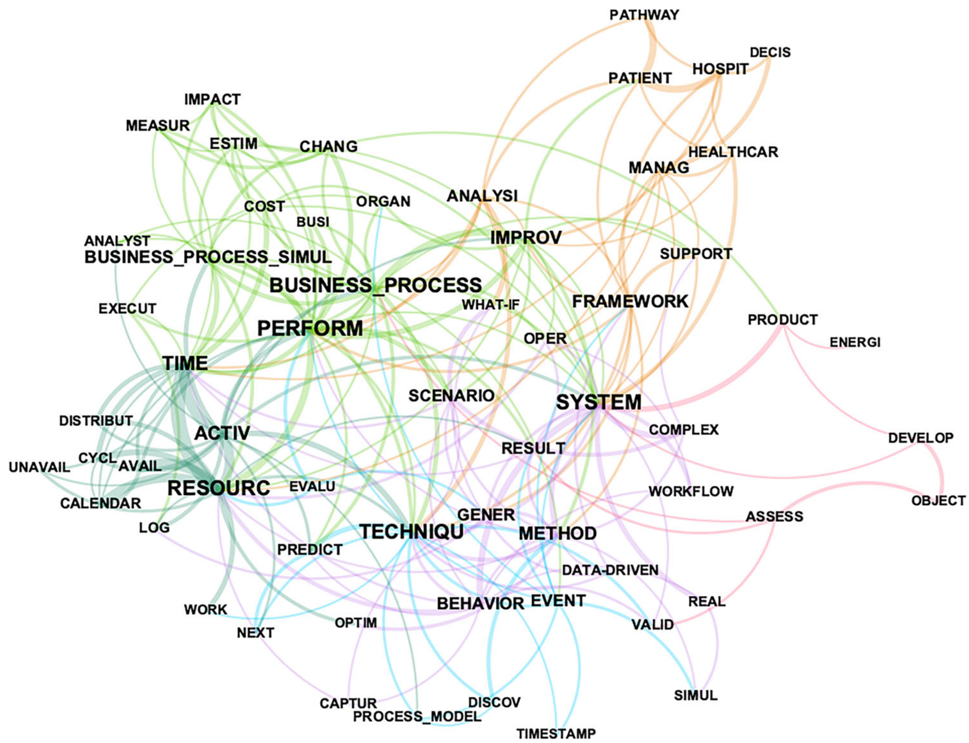


Table 3 describes the top ten cited articles (according to *in-degree* metric) and the nine most influential ones (according to Betweennes centrality metric). Regarding the most cited papers, these are indeed seminal works, i.e., one of the first papers presenting the idea of (semi)automatic discovery of simulation models using process mining techniques [11], the presentation of the ProM tool [28], or two foundational books on the topic [3, 12]. Articles occupying a more central position in the network are articles in healthcare (i.e., [29], [30]), which is one of the main application areas in which process mining has been used most, as well as the presentation article of the Heuristics Miner process discovery algorithm, which has been successfully applied in several areas, and this may explain its central position in the network.

This exploratory phase provides a general idea of the research groups and themes addressed in the survey articles. We leveraged these insights in determining the variables for the coding phase, explained in the following Section.

Table 3 Most cited articles according to *in-degree* (InDeg) and most central ones according to betweenness centrality (BetwC) in the citation network of the final paper set

Metric	Articles
Relevance (InDeg)	Rozinat, 2009 [11]—Camargo, 2020 [31]—Van der Aalst, 2016 [12]—Martin, 2016 [4]—Van der Aalst, 2015 [32]—Estrada-Torres, 2021 [33]—Van der Aalst, 2004 [34]—Dumas, 2018 [3]—Rojas, E., 2016 [35]—Camargo, 2022 [36]
Centrality (BetwC)	Martin, 2016 [4]—Zhou, 2014 [29]—Wynn, 2008 [37]—Leemans [38],—Martin, 2020 [39]—Tamburis, 2019 [30]—Weijters, 2006 [40]—Van der Aalst, 2004 [34]—Van Dongen, 2005 [28]—Van Dongen, 2015 [41]

5 Structured literature review

Overview of Included papers

Most of the 105 papers included in the survey have been published in recent years, reflecting the growing interest in combining process mining and simulation techniques. In fact, 29 articles have been published in the last three-year period (2023–2025), 33 in previous three years (2020–2022), 23 articles in 2017–2019, and the remaining 20 before 2016.

The venue of the selected articles concerns a predominance of conferences (63) over journals (42). Table 4 summarizes the final paper set according to the above-mentioned categories, i.e. time frame and venue.

5.1 Paper focus

Goal The main objective of most papers is the generation of an executable model, i.e., 68 cases. In addition, 5 articles focus only on validation, while articles that intend to support a specific simulation task are 32. Of these, papers may be focused on activity duration estimate (5), resource scheduling modeling (5), while we can identify other specific

Table 4 The final paper set by venue (conference or journal) and time frame (years of publication)

Years	Conference	Journal
2007-2016	[29, 42–53]	[54–60]
2017-2019	[10, 30, 61–75]	[76–81]
2020-2022	[82–91] [8, 36, 92–98]	[31, 33, 99–110]
2023–2025	[111–124]	[125–139]

sub-categories, i.e. conceptual model discovery, simulation log inspection, activity scheduling modeling, arrival rate modeling, automatic parameter update.

Types of simulation The reviewed articles mainly concern simulation of discrete time events (90), and to a lesser extent agent-based (9) and system dynamics (5) approaches, while a paper proposed the combination of both DES and SD.

Goal of the simulation analysis The simulation analysis proposed in the selected papers has two main goals, i.e., validation (40 papers) or scenario analysis (35). In fact, most papers propose a (semi-)automated way to extract a simulation model, whereas the experiments focus on validating whether the output of the discovered simulation model corresponds to reality. Similarly, simulation is performed for decision-making purposes, i.e., the simulation analysis aims to compare a number of scenarios with each other. To a lesser extent, the simulation analysis addressed an optimization task (7), i.e., the goal of the analysis is to find an optimal value for one or more process-related components. In another set of cases, the simulation analysis is used to benchmark the proposed approach to alternative approaches (7). In the remaining papers, either no simulation analysis was reported or no simulation analysis was conducted.

Degree of automation We investigated the degree to which process mining is used to create the simulation model, i.e., is the simulation model created fully automatic or in a semi-automated way. In our survey, 20 papers out of 105 present fully automated systems, i.e., the simulation model is created in a fully automated way. In the majority of studies (85), process mining is used to support specific aspects of the simulation model.

Research sector or industry

Most of our survey involved research conducted on a particular sector or industry (58 cases), rather than general (47). The most represented research domain is healthcare (26 cases). Within this domain, a wide range of subfields is covered, including cardiology, dentistry, emergency departments, epidemiology, hernia surgery, hospitalized patients, neurology, operating rooms, ophthalmology, outpatient clinics, outpatient appointment scheduling, radiology, and stroke management units.

Another prominent sector is manufacturing (12 cases). In addition, several other areas are addressed, including finance (4), construction (3), the purchasing sector (2), education (2), order-related processes (2), logistics (1), mining (1), transportation (1), tax (1), the gas industry (1), and emergency call centers (1).

5.2 Toolings

Simulation tools

The tools used by the reviewed papers are equally distributed between proprietary software (30) and open source (43). In some articles, several software programs were used, while in others, the article did not mention the simulation software used. With regard to the type of simulations, there are some significant differences. In particular, for performing DES the open-source tools are mainly custom or python-based (e.g., SimPy), then CPN Tools, and finally solutions developed at Tartu University (i.e., Primoris, BIMP). On the contrary, proprietary tools involve 14 different vendors.[7] In the case of agent-based simulations, there is a prevalence of two proprietary tools (Anylogic, Arena) over open-source ones (NetLogo, AgentPy, Mesa). Finally, the few cases of SD simulations in our survey are all based on the Vensim tool. An analysis of recent years highlights some interesting differences, revealing that from 2021 onwards Python-based implementations have been steadily increasing. In fact, they were almost completely absent before 2020 (with only one paper using the SimPy library). From 2021 onwards, we identified 15 papers focusing on Python-based libraries, covering both DES (SimPy, Prosimos, RimsTool) and ABM (AgentPy, MESA).

Process mining tools The most widely used tools for process mining, among the articles included in the final selection, are open-source tools, such as ProM (31), and, to a lesser extent, *ad-hoc* tools (19), often exploiting the Python library pm4py (10), bupaR (1), Simod (7), or Declare (2). Proprietary software includes Disco (14), Apromore (9), and ProDiscovery (1).

The temporal analysis highlights a substantial growth in the adoption of process mining software over the past decade. Specifically, the number of studies referring to proprietary tools increased from 2 papers before 2016 to 27 papers after 2017, while those concerning open-source solutions rose from 14 to 39 papers. This trend indicates that software tools have played an increasingly central role in advancing research in the field.

[7] Proprietary software for DES mentioned in the papers include: ADONIS, AutoMod Product Suite, Bizagi Modeler, Bonitasoft, DCR graphs, DeepSimulator, Flexsim, IBM WebSphere BPM, jStrobe, Lanner L-SIM, Lanner Witness, Matlab - SimEvent, Process Modeler, ProModel, Scylla, SimStudio, Simul8.

5.3 Used data and validation

Synthetic vs real-life data An aspect of interest concerns the data used in the research. Some research can exploit real-life data, instead of synthetic datasets, i.e., artificial data able to reproduce the features of the original ones. Moreover, we investigate the public or private nature of such data. In particular, synthetic data are used in 38 papers out of 105, mostly having a private nature (21). Real-life data are used in 85 research papers. The datasets used in the analyzed papers include public (35) and private (9) datasets.

Validation Our review revealed that 36 out of the 105 reviewed papers did not perform any validation. Among the papers that conducted an evaluation, 7 relied exclusively on qualitative validation with domain experts, without providing systematic procedures or guidelines for the validation task. Among the remaining papers, 55 papers relied exclusively on quantitative metrics, while 7 papers integrated quantitative and qualitative validation. Papers whose goal was to generate an executable model often propose to assess the similarity between the output generated by the simulation model and the historical data. Most approaches compare a set of indicators (e.g., cycle times or waiting times), either graphically (e.g., histograms or time-series plots) or analytically (e.g., comparing means, possibly using statistical tests). Some approaches also compare the behaviors allowed by the simulation model and the original log, considering the generated sequences of activities (e.g., [31]). Some authors employ conformance-checking metrics, such as fitness, to evaluate the overall correspondence between the model and the event log (e.g., [43], [79], [93]).

5.4 Simulation modeling tasks

When building a BPS model, a multitude of modeling tasks need to be performed. Table 5 provides an overview of the BPS modeling tasks included in our review compared to Martin et al. [4], an earlier overview of BPS modeling tasks. Note that the latter paper is conceptual in nature and, hence, did not base its overview of BPS modeling tasks on a systematic literature review. Table 5 shows that most BPS modeling tasks listed by Martin et al. [4] also appeared in our review, with queue abandonment condition and unexpected interruptions as exceptions. In addition, some novel BPS modeling tasks also emerged from our review, including waiting time specification and resource workload distribution.

When considering the modeling approach, i.e., how a particular modeling task is performed, the results show that BPS modeling tasks were mainly carried out through the adoption of process mining techniques and domain knowledge (and in some cases a combination of both), as detailed in the next paragraphs.

Process Mining The definition of the control-flow is the task for which process mining is highly adopted (79 out of 105), mostly alone, in one case in combination with domain knowledge [49]. Other relevant tasks performed with process mining are the computation of duration (68), the activity definition (56), the entity arrival rate (49), or the gateway routine logic (44). Figure 4 summarizes the results.

Domain knowledge Some key aspects of process modeling and simulation are addressed only by the intervention of domain experts, in some cases in addition to process mining, in other cases without any other support. In our final paper set, the most frequent tasks addressed by domain experts are the definition of *entity types* (16 articles), and entity attributes (11), entity arrival rate (10), activity definition (14). Domain experts are also still relevant in the definition of resource-related aspects such as requirements (12), roles (10), and schedules (8), as summarized by Fig. 5.

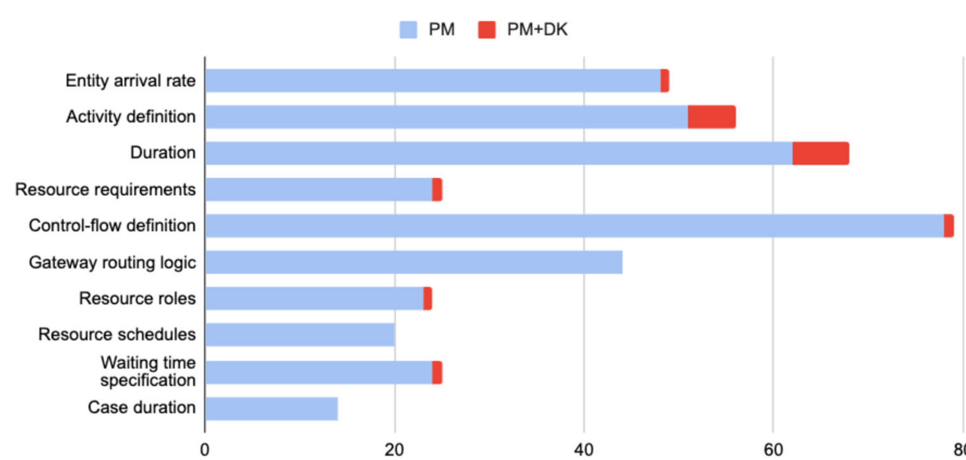
Process mining algorithms The application of process mining techniques to address specific aspects of simulation modeling tasks provided interesting insights. Control-flow definition occurs 79 times, emphasizing the relevance of process discovery in understanding the sequential order of activities in processes. The most used algorithms to discover control flow reveal other interesting insights into their diffusion. Alpha Miner, i.e., the first algorithm in the discipline, was employed in 6 articles, showcasing its application in process discovery. The Heuristic Miner, known for its ability to handle noise and imperfections, was utilized 9 times, highlighting its popularity in real-world scenarios. Inductive Miner, with its emphasis on ensuring soundness in process models, was a choice in 11 papers. Fuzzy Miner, recognized for handling uncertainties, demonstrated its versatility with 12 occurrences. The Split Miner, a technique focusing on subprocess identification, was applied 12 times. The application of algorithms is often linked to the use of tools that adopt them, as in the case of Disco and Fuzzy Miner, Apromore and Split Miner, ProM for the others. Custom algorithms implemented from the researchers occur 8 times in our survey.

Process mining has also been used to determine the duration of processes (68), a crucial factor in modeling realistic scenarios. Activity definition has been addressed via process mining in 46 articles, underlining the importance of accurately representing individual tasks in simulation models. The definitions of entity arrival rate (49), gateway routing logic (44), and resource requirements (25) showcase the multifaceted nature of process mining techniques. Further automatic techniques involved the waiting time specification (25), resource roles (24), entity attributes (13), and resource schedules (20).

Table 5 Overview of the BPS modeling tasks appearing in our review compared to Martin et al. [4]

Modelling task	Description	Appearing in Our review	Martin et al. [4]
Entity attributes	Specifying the characteristics of an entity and their entity-specific attribute values [4]	✓	✓
Entity types	Specifying entity profiles, representing a group of entities with similar attribute values [4]	✓	✓
Entity arrival rate	Specifying the rate at which new entities arrive in the process [4]	✓	✓
Activity definition	Specifying the activities to be included in the BPS model [4]	✓	✓
Activity duration	Specifying how long executing an activity takes [4]	✓	✓
Resource requirements	Specifying the resource(s) needed to perform an activity [4]	✓	✓
Queue discipline	Specifying the order in which queueing entities are handled [4]	✓	✓
Interruptibility	Specifying whether an activity can be interrupted mid-execution due to a foreseen situation [4]	✓	✓
Control-flow definition	Specifying the order of activities that an entity can follow through the process [4]	✓	✓
Gateway routing logic	Specifying the routing logic followed at a decision point [4]	✓	✓
Resource roles	Specifying groups of resources that perform similar activities [4]	✓	✓
Resource schedules	Specifying a resource's presence for a process [4]	✓	✓
Unavailability handling procedure	Specifying how a period in which a resource is unavailable is handled if it starts while the resource is performing a non-interruptible activity [4]	✓	✓
Entity handling procedure	Specifying the number of entities on which a resource performs an activity simultaneously or successively [4]	✓	✓
Queue abandonment condition	Specifying conditions under which entities will prematurely leave the queue without being served [4]	✗	✓
Unexpected interruptions	Specifying unforeseen interruptions of an activity mid-execution [4]	✗	✓
Waiting time specification	Specifying the waiting time that needs to be respected in a particular stage of the process	✓	✗
Multitasking	Specifying how a resource divides its attention when executing an activity on multiple entities simultaneously	✓	✗
Entity flow time	Specifying the end-to-end flow time of an entity	✓	✗
Looping behavior	Specifying the looping behavior that arises in the process	✓	✗
Resource workload distribution	Specifying how workload is distributed between resources in the process	✓	✗
Resource cooperation relationships	Specifying cooperation relationships between resources	✓	✗

Fig. 4 Distribution of main simulation modeling tasks performed using process mining techniques alone (PM) or even with domain knowledge (PM + DK)



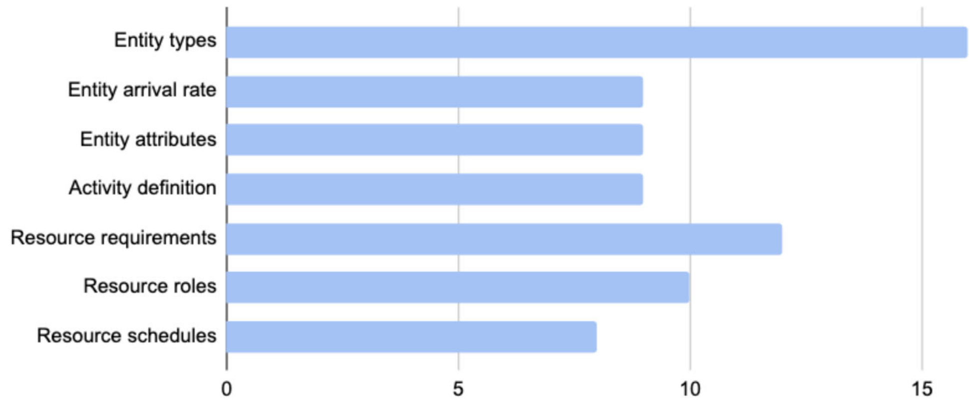


Fig. 5 Distribution of the main modeling tasks addressed only by means of domain knowledge

5.5 Temporal trends in the reviewed literature

This section examines the temporal trends in the reviewed literature, focusing on whether the main characteristics of the surveyed studies remain consistent throughout the period analyzed or exhibit changes over time. Overall, several interesting patterns emerge from the temporal evolution of the field. As highlighted in Table 4 at the beginning of this section, the distribution of publications shows a clear growth in recent years. In particular, the interest reflects the increasing maturity of the integration between process mining and simulation, as well as the growing availability of tools and event-log datasets. While most papers are technically oriented throughout the entire time span, in the most recent years (mainly after 2023) a small number of contributions adopt a more managerial perspective. This may suggest a gradual transition from methodological research toward practical and decision-support applications. Regarding the goal of the studies, earlier work mainly focused on scenario analysis and validation. Over time, additional objectives such as optimization and benchmarking become more common, indicating a diversification of research goals and evaluation strategies. Consistently, the literature suggests a progressive evolution of the field, moving from early technical explorations based on established simulation tools toward more automated, data-driven, and domain-oriented approaches supported by modern process mining frameworks and programmable simulation environments. With respect to simulation tools, early studies (2007–2015) mainly relied on classical tools such as CPN Tools, Arena, and Simul8, while more recent work increasingly adopts Python-based solutions (e.g., SimPy, AgentPy, Mesa) and custom tools. This shift suggests a growing preference for flexible and programmable simulation environments. A similar evolution can be observed in the process mining tools adopted: while ProM remains one of the most frequently used tools throughout the entire period, recent studies show an increasing use of PM4Py, Apromore, and custom frameworks, reflecting the expansion of the process mining software solutions. Considering the degree of automation, most studies adopt semi-automated approaches, where process mining supports specific modeling tasks. Fully automated approaches appear more frequently in recent years, reflecting ongoing efforts toward automated simulation model generation from event logs. In terms of application domains, most studies remain domain-specific, with healthcare emerging as the most represented area. Other sectors include manufacturing, finance, construction, logistics, and transportation. As discussed in previous sections, most studies rely on real-life event logs, often combined with synthetic datasets for experimentation. The use of synthetic data alone is relatively limited, suggesting that empirical validation using real operational data plays an important role in this research field. Finally, quantitative validation is widely adopted across the studies, whereas validation through domain experts appears less frequent. Overall, the last-mentioned features remain broadly consistent over time, indicating a relatively stable pattern in the selected literature without significant shifts in their distribution. Table 6 summarizes some features of interest.

6 Discussion and outlook

Historically, BPS and process mining were two distinct research fields that developed independently from each other. While both focus on process analysis and aim to support decision-making, they take a different perspective. Traditionally, process mining research developed methods to extract insights into business processes from historical process execution data. Examples of such insights include the order in which activities are performed in reality, the extent to which real-world process behavior matches a normative model of how the process should be performed, and how long the different parts of the process take. These types of analysis have a *backward-looking focus*: taking historical data as input, insights are gathered in the as-is process that can, for instance, surface process performance issues, such as bottlenecks or inefficiencies [140]. Conversely, BPS intrinsically

Table 6 Temporal distribution of selected features across the surveyed studies

Number of papers			2007–2016 20	2017–2019 23	2020–2022 33	2023–2025 29	Total 105
Features of interest	Data	Synthetic	6	6	11	15	*38*
		Real	14	18	28	25	85
		Public data (both)	2	5	15	22	44
	Simulation tool	FOSS/academic tools	7	2	12	5	26
		Python-based	0	1	5	11	17
		Proprietary	5	8	12	5	30
	PM tool	Proprietary SW	2	6	7	9	24
		Open Source SW	13	10	13	16	52
	Domains	Administrative-Financial	4	2	3	4	13
		Industrial-Infrastructures	9	11	17	9	46
		Healthcare	5	9	11	1	26
	Validation	Domain experts	2	3	4	5	14
		Quantitative	6	14	23	19	62
		No validation	14	9	8	5	36

has a *forward-looking focus*: it enables organisations to analyze and compare alternative configurations of a future to-be process before implementing it in practice [4, 6]. This shows that process mining and BPS provide complementary support to organisational decision-making: while process mining can highlight performance issues, BPS can help to evaluate potential solutions to address them.

The combined use of process mining and BPS enables organisations to simulate future configurations of a business process, while relying heavily on historical process execution data when developing the simulation model [4]. Our paper thoroughly analyzed the body of knowledge on the use of process mining in a BPS context.

While our results clearly show the progress and increasing maturity of research on the intersection between process mining and BPS, some critical open challenges remain to be addressed. In the following, we elaborate upon the challenges that arise from our analysis and highlight pertinent research avenues for future research.

Validation of simulation models Despite model validation representing a crucial step to obtain reliable results, a substantial part of the reviewed papers (36 out of 105) do not provide any validation of the proposed approach. For the papers that conducted validation, our analysis revealed two main validation strategies, often performed together. The first, more widely adopted, strategy is to compare the simulation outcome with available historical data. This approach closely resembles validation procedures commonly adopted within the simulation community. However, we observe a lack of systematic, shared procedures for validation, including the selection of the metrics and the methods used to perform the actual comparison. Different studies employ ad-hoc metrics, possibly tailored to the domain at hand. Similarly, different comparison strategies are employed, from comparing plots to quantifying the distance between the simulated and the historical values of selected indicators to performing statistical tests. A second validation strategy focuses on the *quality* of a process model, i.e., the extent to which the model provides an accurate representation of the corresponding process. This is a long-standing challenge within the Business Process Management field, where this aspect of process models is usually referred to as *semantic quality* [3], and traditionally qualitatively assessed through workshops or interviews with process stakeholders. In our review, 14 of the 105 papers included a qualitative evaluation; however, they often provided little or no explanation of how the evaluation was conducted, making it impossible to judge the reliability of the results. In general, qualitative validations are challenging to standardize, and their results are subject to interpretation. Relying exclusively on domain knowledge also carries well-known drawbacks due to human bias, often discussed within the BPM literature [141], making more quantitative and objective methods desirable. Within the PM field, and in particular within the conformance checking branch, quantitative metrics have been introduced to assess the quality of a given model with respect to the behavior recorded in the event log, treating the latter as a (possibly incomplete) snapshot of the real process behaviors [142]. Some of the reviewed approaches use these metrics to assess the quality of the generated models relative to the original event log. However, obtaining an holistic assessment of process model quality that goes beyond fitness is still a challenging task. For example, Tax et al [143] show that widely used precision metrics violate basic axioms and behave inconsistently across logs and models, while Syring et al [144] demonstrate that many fitness, precision, and generalization measures are defined ad-hoc and fail to satisfy essential correctness propositions.

Taken together, these insights suggest the need for *coherent methodological foundations for validating PM-based BPS models*, capable of integrating the model assessment with respect to stakeholder expectations and historical data. Both the overall quality of the model per se and its capability of generating outcomes in line with the underlying process should be considered.

It is worth noting that the topic of simulation model validation represents a challenging but well-known topic within the broader simulation discipline [145]. Surprisingly, however, we found little connection in the reviewed papers to simulation principles and methodologies commonly used for validation tasks. We argue that leveraging and adapting such validation methodologies could benefit research on the use of process mining in a simulation context.

Assisted support for accurate models Semi-automated approaches significantly outnumber the fully automated approaches. This suggests that it is far from trivial to retrieve a complete simulation model from an event log in a fully automated way. Our analysis revealed three main factors contributing to this complexity. The first factor is that research on the use of process mining in a simulation context is highly concentrated around a subset of the identified simulation modeling tasks, such as entity arrival rate, activity duration, and control-flow discovery. For many others, limited to no support is available for performing them using PM. This holds in particular for most tasks related to queues and to resources. Such a discrepancy can partly be explained by the lack of data on these aspects, particularly regarding resource behavior, which might be spread over different systems or not tracked at all. Typically, domain knowledge will be needed to address knowledge gaps that emerge from the data. However, it is worth noting that in most of the analyzed papers, these tasks are abstracted altogether, which can hamper the accuracy of the resulting simulation models. We argue that the rapid uptake of *Large Language Models* (LLMs) offers a promising strategy to tackle this challenge. Several studies have highlighted the potential (and challenges) of leveraging LLMs for different BPM and PM tasks (see, e.g., [146], or [147]), sparking a strong interest in the topic. Within the BPS context, LLMs might be employed to leverage unstructured but relevant information on the process from, e.g., job advertisements, handbooks, communication logs such as e-mails or chats between process participants, interviews made with the process participants, and so on. These heterogeneous sources often provide valuable information on the process, including (but not limited to) resource behavior and roles, which may be missing in structured event logs and can support the design of more accurate simulation models. However, identifying relevant information within large document collections can be highly time-consuming and labor-intensive. Large Language Models (LLMs) are well-suited to this challenge, thanks to their ability to rapidly scan, prioritize, and extract essential content. A few studies already show the application of LLMs to unstructured texts to automatically derive a process model, either directly [148] or by integrating them into the pipeline of standard process discovery algorithms leveraging structured data [149]. We argue that this is a promising direction to automatically distill more accurate simulation models.

A second threat to BPS accuracy is related to the limitations of classic PM approaches to take into account the *interaction among processes*. Almost all the reviewed BPS approaches follow the traditional *case-centered* paradigm, where a single case notion is selected to extract process traces in an event log. However, recent studies highlight several drawbacks of such a paradigm [149, 150]. In reality, events often interact with multiple objects, corresponding to different candidate identifiers. To create a traditional process model, the event data needs to be "flattened", selecting one specific identifier. However, this often leads to disconnected views of the process, corresponding to different choices for the case identifiers, which do not properly represent the reality. In this paradigm, process executions are considered in isolation; in reality, instead, multiple processes usually interact with each other, and often involve multiple business objects that might interact through shared events. This information is, however, lost when flattening the event logs. Event log flattening also leads to known technical problems such as *convergence* (i.e., events associated with multiple objects and duplicated across multiple traces) and *divergence* (i.e., multiple instances of the same activity within a case). These issues hamper the reliability of the extracted models. A promising research avenue to address these limitations is given by the introduction of the *Object-centric Process Mining* (OCPM) paradigm, which aims at overcoming limitations of case-centric approaches and which is quickly gaining popularity within the BPM and PM communities. However, at the time of this review, we found only one paper leveraging the Object-centric (OC) paradigm for BPS [113]. We argue that the development of OC simulation models represents a promising avenue for developing accurate simulation models that can account for the complex interactions across different processes in the real world.

A final factor that contributes to the complexity of retrieving a simulation model from an event log is the lack of tools that implement (semi-)automated methods, even for modeling tasks for which such methods are available. The analyst is still largely responsible for selecting the methods to use to pre-process the event log, discover the control flow, the gateway probabilities, etc. These are complex, time-consuming and error-prone tasks that require extensive interdisciplinary knowledge. Our review pointed out that little attention has been devoted to developing frameworks to streamline the development of simulation models. A notable exception is the Simod suite [31], even though the process characteristics that can be modeled remain limited. Future research aimed at developing tailored tools is essential to handle the intricacies of simulation model development effectively. Addressing such a research gap is vital to enable the development of generalisable business process simulation approaches that a variety of organisations can easily adapt for processes with different characteristics.

Model interpretability A recent trend in literature is leveraging machine learning and deep learning to accurately capture complex, nonlinear relations to either support specifying modeling tasks, e.g., interarrival times, branching probabilities in process decision points, etc, or to automatically obtain a completely data-driven simulation model. Despite the high accuracy of the models returned by these systems, their application for business process simulation purposes is hampered by their black-box nature. These models are not interpretable by humans, which limits their practical relevance for classic simulation tasks such as what-if scenarios. Recent approaches have started investigating hybrid solutions to leverage the benefits of black-and-white-box approaches. However, this trend is in its early stages of development. It is worth noting that issues related to the use of black-box models have rapidly gained increasing attention in recent years within the broader Artificial Intelligence field, leading to the development of *explainable AI techniques* [151]. A parallel growing trend can be found within the BPM and PM communities, where several *explainable predictive process monitoring* (xPPM) were recently proposed with the aim of delivering human-interpretable explanations of predictions on future process behaviors [152]. These approaches provide a promising means to expand the application of machine learning techniques to BPS, since they enable the human analyst to unravel the inner workings of the black-box models and understand what drives their decisions, which is crucial for validation purposes. Furthermore, combining these techniques with recently proposed approaches to generate synthetic event logs including analyst-defined behaviors [153] can pave the way to train DL models in different scenarios, thus enabling what-if analysis. Notably, this aspect is investigated by one of the most recent approaches in our review [122].

Static models Business processes are likely to evolve over time for several reasons, including updates in laws and regulations, new market trends and changes in the geopolitical situations. This issue has been already recognized within the process mining community, where several approaches have been proposed to deal with process *concept drift* [154]. To ensure reliable results, simulation models should be able to capture such concept drift and adapt accordingly. However, this is far from trivial. Notably, none of the reviewed papers investigated issues related to when and how to update simulation models. Hence, this constitutes an open avenue for future research. It is worth noting that a growing number of recent studies have addressed issues related to concept drift in the online implementation of predictive process monitoring approaches. The core idea of these approaches is to retrain the predictive models to reflect changes in the underlying process. Common strategies are periodic retraining [155], use of incremental classifiers [156], or retraining triggered by concept drift detection [157]. We argue that similar strategies could be investigated to determine when to update a BPS model, thus improving the adaptability of these systems.

Agent-based versus discrete-event modeling An interesting aspect concerns the types of simulation referred to in process mining, whereas the discipline has largely adopted discrete-event simulation. Few works have dealt with System Dynamics [105], which is one of the most classic simulation techniques. However, in the field of simulations, an increasing space has been occupied by agent-based approaches and hybrid simulations (whose design more and more often leverages Machine Learning approaches [158]); however, these approaches do not appear frequently in the field of process mining, as shown by our review which found only 10 papers using the agent-based paradigm out of 105. A possible explanation for the prevalence of discrete-event simulations is related to the simplicity and familiarity of the industrial sector, where it is a well-established methodology and may be more familiar to practitioners in, for example, manufacturing or logistics. In addition, processes appear to be naturally event-driven and follow clear sequential paths, so it is apparent that a discrete-event approach may be easier to apply and understand. However, this apparent linearity is often questioned even by the process mining algorithms themselves, as shown by the *spaghetti-like* representations that indicate a much greater complexity than domain experts believe. Conversely, agent-based methods have been shown to excel in modeling complex systems with numerous interacting entities and emergent behaviors [159]. Therefore, an intriguing future research direction lies in the construction of agent-based simulations from event logs, particularly through the development of *agent discovery from event logs*, where behavioral rules, interaction patterns, and decision logics of agents are inferred directly from process data [160, 161]. Some reviewed papers investigate this direction, with promising results (e.g., [66]). Nevertheless, this is still an under-investigated topic. A related challenge concerns the validation and calibration of agent-based models using process mining techniques, where conformance checking and performance analysis could be leveraged to systematically compare simulated behavior with observed event-log traces and iteratively adjust model parameters to improve behavioral fidelity. Finally, it seems plausible that the choice between DES and ABM should be based on the specific characteristics of the system under study and the objectives of the simulation.

7 Conclusions

This work reports on a systematic literature review on process mining techniques to support BPS. The traditional SLR methodology is further enriched with network analysis to offer a complementary structural perspective on the research landscape. In response to RQ1, the network analysis enabled us to identify the main research topics, including process modeling, business process management, resource and time management, validation and evaluation, healthcare applications, and industrial optimization. The research community emerges as heterogeneous and decentralized, characterized by several cohesive cores alongside smaller clusters. Moreover, the analysis highlights seminal methodological contributions and structurally central studies that have shaped the development of process mining–simulation integration.

In response to RQ2, the survey results provide a structured framework highlighting common process mining techniques, tools employed to support business process simulation projects, and the application domains where these techniques are most commonly utilized. Our analysis led to an extension of state-of-the-art framework encompassing the most important BPS task [4], to incorporate recent trends usually neglected in previous studies but which have been gaining increasing importance, like the modeling of resource behaviors.

We believe that the outcomes of the analysis provide an interesting contribution for both practitioners and academics. From the viewpoint of practitioners, Sect. 5 offers a comprehensive overview of the available tools and techniques that can aid in a specific BPS modeling task. This information is valuable for conducting their own simulation study effectively. From the researchers' perspective, the analysis revealed several open challenges, discussed in Sect. 6, which delineate pertinent avenues for future research in the field.

8 Search queries

The following search queries were used to retrieve relevant literature in the different databases:

- Scopus:
  TITLE-ABS-KEY (("PROCESS MINING" OR "EVENT LOG" OR "EVENT-LOG") AND simulation) AND (LIMIT-TO (DOCTYPE,"cp") OR LIMIT-TO(DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"ch") OR LIMIT-TO(DOCTYPE,"bk"))
- Web of Science:
  ALL=(("process mining" OR "event log" OR "event-log") AND simulation)
- IEEE Xplore:
  (("All Metadata":"process mining" OR "All Metadata":"event log" OR "All Metadata":"event-log") AND ("All Metadata":simulation))
- ACM Digital Library:
  Abstract:("process mining" OR "EVENT LOG" OR "EVENT-LOG")) AND Abstract:(simulation) "filter": ACM Content: DL

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Data Availability All the SLR process files, coding, images are publicly available in the following repository: https://t.ly/VIlGc.

Declarations

Conflict of interest The authors declare no conflict of interest.

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