On the Integration of Business Process Simulation and Predictive Process Monitoring

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Abstract. Business Process Simulation (BPS) and Predictive Process Monitoring (PPM) constitute the two primary techniques for forward-looking analysis in Business Process Management (BPM). While BPS enables counterfactual evaluation of alternative process configurations, PPM focuses on forecasting the evolution of ongoing process instances under the current process configuration. Although recent research increasingly combines both techniques, their integration remains conceptually fragmented and lacks a systematic synthesis, potentially obscuring opportunities to leverage their complementary strengths for advancing forward-looking BPM. To address this gap, this paper presents a structured literature review of 32 studies that integrate BPS and PPM. We analyze the identified studies along three perspectives: (i) the tasks addressed through integration, (ii) the conceptual integration patterns, that is, how both techniques are combined, and (iii) the resulting synergies. The review reveals that most existing approaches combine BPS and PPM asymmetrically and in a simulation-oriented manner, whereas tighter, decision-oriented couplings remain underexplored. Based on these findings, we derive a future research agenda that highlights how integration may help address known challenges of both techniques and outlines directions toward more adaptive and decision-oriented forward-looking BPM.

Keywords: Business Process Simulation · Predictive Process Monitoring · Systematic Literature Review · Decision Support · Forward-Looking.

1 Introduction

In times of increasing uncertainty, organizations require analytical techniques that support decision-making with respect to the future behavior of their business

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processes. Such techniques aim to infer how processes are expected to evolve based on historical execution data, thereby moving beyond merely descriptive and retrospective forms of process mining. In the literature, these approaches are referred to using different terms, including *forward-looking process mining* [46], *predictive process analysis* [10], and *proactive process mining* [44]. Despite these different labels, they share a common focus on predictive and simulation-based capabilities for decision support under future uncertainty, realized through business process simulation (BPS) and predictive process monitoring (PPM).

PPM focuses on predicting the future behavior of individual—currently running—process instances. Typical tasks include predicting the remaining execution time, next activity, or the likelihood of different outcomes [8]. BPS, in turn, is used to evaluate the impact of process changes on key performance indicators such as cycle time or resource utilization, by executing a simulation model under different what-if scenarios [10]. While differing in scope and level of abstraction, both BPS and PPM are closely intertwined in informing decisions about possible future process behavior from observed process executions.

Traditionally, BPS and PPM have largely evolved in separation; however, recent work indicates increasing methodological convergence between the two techniques. A significant line of research integrates PPM into BPS models to estimate or refine simulation parameters, thereby improving the realism and accuracy of simulation (see, e.g., [6, 35, 55]). In addition, PPM has been used as a downstream task to assess the quality of simulation models [41]. Conversely, simulation techniques are increasingly embedded within prescriptive monitoring [13, 57] and process optimization [36] approaches to evaluate alternative decision scenarios. These developments illustrate that integrating simulation and prediction can enhance forward-looking process analysis and enable decision-support capabilities that neither approach could achieve in isolation.

Despite the growing convergence of BPS and PPM and their potential to enhance forward-looking process analysis, there is no *systematic* understanding of how the two can be combined to support decision-making. Most contributions focus on one technique and occasionally use the other in a supporting role, without explicitly analyzing their integration patterns and synergies. Only a few works adopt a broader perspective. Poll et al. [44] conceptualize forecasting as a form of forward-looking process analytics positioned between simulation and prediction, but do not analyze concrete integration opportunities. Chapela-Campa and Dumas [10] argue that backward-looking process mining provides the foundation for forward-looking analysis, encompassing both simulation and prediction, which in turn enable prescriptive analytics and augmented process execution. However, they treat simulation and prediction largely as independent capabilities and do not examine how these can be systematically integrated. As a result, no consolidated view exists on how simulation and prediction have been combined, what synergies they enable, or how their joint use can be systematically advanced.

Recognizing this gap, this paper provides a structured analysis of the integration between BPS and PPM to clarify the current research state and identify directions for strengthening forward-looking process analysis capabilities. To this end, we conduct a systematic literature review of works that combine simulation and prediction in BPM and analyze them along three research questions:

- **RQ1:** What tasks are addressed by integrating BPS and PPM?
- **RQ2:** How are BPS and PPM conceptually integrated?
- **RQ3:** Which synergies are achieved through the integration of BPS and PPM?

In this sense, RQ1 addresses *what* is studied, RQ2 focuses on *how* both techniques are integrated, and RQ3 investigates *what* is achieved through the integration. Building on these findings, we discuss implications and outline directions for future research on integrating simulation and prediction in BPM.

In the remainder, Section 2 provides background and related work on BPS and PPM, Section 3 outlines our research method, Section 4 presents the review findings, Section 5 discusses implications for future research, and Section 6 concludes the paper.

2 Background and Related Work

We define the scope of simulation and predictive capabilities in BPM for proactive decision-making and review related surveys to identify existing research gaps.

Business process simulation (BPS).

Scope. BPS is a forward-looking BPM technique for analyzing and predicting the impact of potential process changes, thereby supporting process design and improvement decisions. It is commonly used for ex-ante evaluation by executing a simulation model and performing what-if analyses of key performance indicators (KPIs) such as cycle time, waiting time, cost, and resource utilization [50, 54].

Input. The inputs to BPS depend on the simulation paradigm. The most common paradigm, discrete-event simulation, requires a simulation model consisting of (i) a process model (e.g., BPMN or Petri net) and (ii) simulation parameters such as activity time distributions, arrival rates, branching probabilities, and resource availability [50, 54]. Traditionally, simulation models were constructed manually. More recently, data-driven approaches derive process models and estimate simulation parameters directly from event logs, increasingly leveraging machine learning techniques (see, e.g., [6]).

Methodology. BPS comprises multiple simulation paradigms, most prominently discrete-event simulation (DES) [24], agent-based simulation (ABS) [28], and system dynamics (SD) [45]. For example, in DES, the simulation model is executed repeatedly to obtain statistically reliable estimates of performance indicators through multiple runs and confidence intervals.

Output. The output of BPS are simulated event logs describing how process instances unfold under specified process changes or interventions. These logs enable further analysis, such as KPI computation to compare alternative scenarios.

Predictive process monitoring (PPM).

Scope. PPM is a forward-looking BPM technique that predicts the future behavior of ongoing process executions at runtime by forecasting subsequent events or outcomes as early as possible, thereby supporting operational decisions such as resource allocation and scheduling optimization [14, 33].

Input. The primary input for training PPM models is an event log containing historical process executions. Some approaches additionally incorporate process models or contextual data as supplementary inputs [8, 33].
Methodology. PPM follows a two-phase pipeline consisting of *model training* and *runtime inference*. During training, completed process executions are transformed into prefixes to capture partial execution states at different points in time. These prefixes are encoded into feature representations suitable for predictive modeling. Modeling approaches include machine learning, statistical methods, annotated transition systems, and hybrid approaches. During inference, the trained model is applied to ongoing executions to generate predictions, which are continuously updated as new events are recorded [8, 14].
Output. PPM produces a predicted value or probability distribution for a target attribute, which may be numerical, categorical, or boolean. Typical targets include remaining time, next activities, process outcomes, performance indicators, and risk or compliance violations [8, 14, 33].

While BPS and PPM have traditionally been studied separately, recent work also combines them. Our review shows that this integration is not merely additive: it gives rise to specific roles and interactions that cannot be observed when studying both techniques in isolation, for instance, when predictions about ongoing cases are combined with simulation to evaluate alternative interventions for decision support.

Related surveys. Several surveys review predictive and simulation capabilities in BPM. Existing work either focuses on simulation, covering methodological trends, hybrid models, and AI-supported simulation [2, 3, 24, 26, 27, 38, 50], or on prediction, covering PPM methods, deep learning, AI in BPM, and prescriptive monitoring [8, 14, 17, 30, 33, 39, 47, 58]. However, these surveys treat BPS and PPM in isolation. A smaller number of surveys adopt a more integrative perspective. Poll et al. [44] frame both PPM and BPS under the notion of *process forecasting*, but place stronger emphasis on PPM and do not clearly distinguish the two paradigms in terms of their objectives, underlying modeling paradigms, and analytical workflows. Chapela-Campa and Dumas [10] position both BPS and PPM within a broader capability framework for data-driven BPM that ranges from descriptive and predictive analytics to prescriptive optimization and augmented process execution. They highlight the different but complementary roles of BPS and PPM, positioning both in the predictive analytics layer. However, neither survey provides a systematic account of how BPS and PPM can be combined methodologically for decision support.

In contrast, we focus explicitly on their combination by identifying and classifying existing integration patterns and synthesizing the synergies they enable for forward-looking process analysis.

3 Research Method

To identify and select relevant literature, we followed a structured, multi-stage review process based on Kitchenham and Charters [29] comprising: (i) scoping

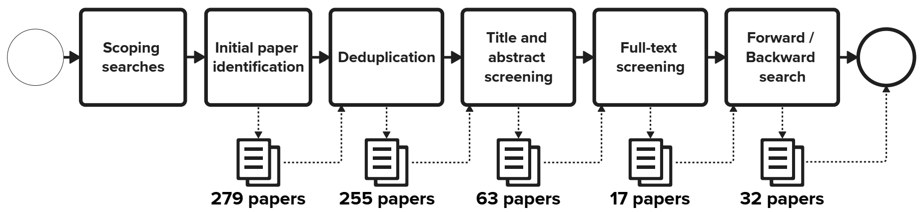

Fig. 1: Overview of the systematic literature review process.

searches, (ii) initial paper identification, (iii) deduplication, (iv) title and abstract screening, (v) full-text screening, and (vi) forward/backward search. Figure 1 presents a flowchart summarizing the search and selection procedure.

Scoping searches. Scoping searches were first conducted across multiple databases to map the existing body of literature. These searches also informed the development and iterative refinement of key methodological components, including the search query and the inclusion and exclusion criteria.

Initial paper identification. The literature search dates to Jan. 9, 2026.

Query. We used the following search query: ("process mining" OR "business process") AND (simulation OR "digital twin" OR "what-if analysis") AND (predictive OR forecast$ OR proactive).

Databases. We conducted a query-based search across the following digital libraries—(a) Web of Science, (b) ACM Digital Library, and (c) IEEE Xplore—to retrieve relevant conference and journal papers. To account for outlets not contained in the three databases above, we follow Martin and Beerepoot's methodology [34] and consider Google Scholar as a secondary database, accounting for its first 100 results, sorted by relevance. In total, we collected 279 papers from all four databases.

Deduplication. The initial paper set contained duplicates due to overlap across databases. The 24 identified duplicates were removed, leaving 255 papers.

Title and abstract screening. The remaining papers were screened based on title and abstract by applying the following inclusion and exclusion criteria.

Inclusion criteria.

- IN1: The paper proposes an approach that combines simulation and predictive capabilities based on business process execution data.
- IN2: Both simulation and prediction constitute central elements of the proposed approach rather than peripheral or auxiliary components.

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 published in a peer-reviewed scientific journal or in peer-reviewed conference proceedings.
- EX4: The paper is a literature review, tutorial, keynote, one-pager, executive summary, abstract, editorial, research proposal, expert interview study, poster, call for papers, table of contents, or other opinion-based qualitative work.

– EX5: The paper has been extended by a more recent paper included in the selection that has a highly similar core contribution.
– EX6: The application domain of the paper is not related to BPM.

Title and abstract were screened independently by two members of the research team. In case of disagreement, a discussion took place to reach a consensus. In case of doubts, a conservative approach was used and the paper was taken along to the next stage. At the end of this stage, 63 papers were retained.

Full-text screening. The remaining papers were screened based on their full texts using the same inclusion and exclusion criteria outlined above. Again, each paper was reviewed independently by two researchers, and disagreements were resolved through discussion. The full-text screening resulted in 17 papers. Most exclusions at this stage resulted from a paper's failure to meet the inclusion criteria, particularly because simulation and prediction were not both central to the paper's core contribution (IN2)[6].

Forward/Backward search. Finally, we conducted forward and backward citation searches on the 17 selected papers, which identified an additional 15 relevant studies. This resulted in a final set of 32 publications.

Data extraction. To answer our three research questions, we constructed an extraction form for each question. For answering both RQ1 and RQ3, we inductively coded the reported tasks and synergies. In contrast, for answering RQ2, we deductively coded how BPS and PPM are integrated based on pre-defined integration patterns, which we will present in Section 4.3.

4 Results

This section presents the findings of our literature review on the integration of BPS and PPM. First, Section 4.1 provides a bibliographic overview of the selected studies. Sections 4.2–4.4 then address the three research questions, before Section 4.5 synthesizes the main findings. A detailed overview of the findings discussed in this section can be found in our publicly available GitHub repository[7].

4.1 Bibliographical Overview of Selected Studies

Figure 2 shows the amount and type of included publications over time. In total, 32 relevant papers were identified. More than two-thirds of these studies were published in or after 2020, indicating that research at the intersection of BPS and PPM has gained increasing attention in recent years.

Regarding publication outlets, 23 studies appeared in conference proceedings and nine in journals. The most common venues are the International Conference

[6] Interestingly, a substantial share of simulation-oriented studies uses the term "prediction" to describe the evaluation of alternative process configurations, which we classify as counterfactual (what-if) analysis, i.e., the classical BPS task. As a result, several papers appeared in the abstracts to integrate BPS and PPM, whereas the full-text review revealed that this impression was largely driven by terminological differences.

[7] `https://github.com/robert-l-b/slr_BPS_x_PPM`

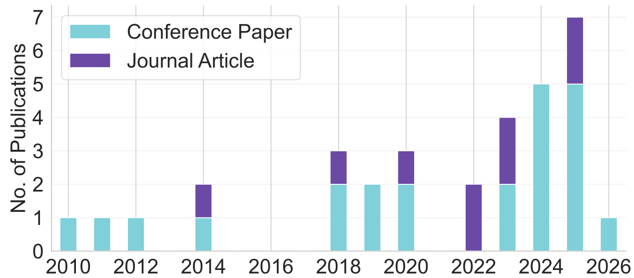

Fig. 2: Overview of relevant studies according to publication year and type.

on Business Process Management (BPM) with nine papers, followed by the International Conference on Process Mining (ICPM) and the Winter Simulation Conference (WSC), each with four papers. Among the journals, Process Science appeared most frequently with two papers, while the remaining articles were published in, e.g., Information Systems and the Journal of Simulation. This concentration suggests that research on the integration of BPS and PPM is primarily disseminated through specialized venues in the BPM and simulation communities.

4.2 RQ1: Tasks Addressed by Integrating BPS and PPM

From the selected papers, we derived three tasks, partly further divided into subtasks, that are addressed through the integration of BPS and PPM. This analysis clarifies for which types of problems the integration is employed and assesses whether these extend beyond the capabilities of traditional simulation or prediction. We identified these tasks inductively by coding the primary problem addressed in each paper. In the following, we describe these tasks and discuss them in the context of forward-looking process analysis.

Observed tasks. Among the 32 papers, 23 address process simulation, four focus on predicting future process performance, and five address prescriptive tasks.

Simulate the process. For 23 papers, the primary task is process simulation. Based on whether the papers specifically target the analysis of process changes, we distinguish two subtasks: *as-is simulation* and *what-if simulation*. Fourteen papers focus on as-is simulation, i.e., simulating the current process without specifically analyzing the effect of process changes [4, 7, 20, 23, 28, 31, 32, 35, 37, 41, 43, 48, 55, 56]. Nine papers focus on what-if simulation, i.e., simulating the process under changes to analyze their effect on performance. Of these, five apply what-if simulation to a specific application domain [9, 18, 19, 25, 53], such as care pathway design [19], tax policy simulation [53], or supply chain risk assessment [25]. The remaining four propose approaches specifically designed for what-if simulation [5, 6, 40, 45]. Note that the boundary between these two subtasks is not always sharp, as several as-is papers mention what-if analysis as a motivation but focus their contribution on simulation accuracy rather than on analyzing the effects of changes.

Predict future process performance. Four papers address prediction tasks, mainly focusing on forecasting performance indicators. Three papers target specific applications, including predicting energy consumption [11], security events [49], and equipment uptime [51]. One paper discusses performance prediction in general terms without a specific application focus [52].

Prescribe future actions. Five prescriptive papers go beyond simulation and prediction and explicitly aim to support decision-making. Four papers focus on prescribing the next best activity [13, 42, 57], resource [42], or intervention [12], typically at the case level and with the goal of improving specific KPIs. In contrast, one paper considers prescription at the process level, optimizing the overall process rather than recommending actions for individual cases [36].

Discussion. The primary finding for RQ1 is that a significant majority of the literature (84%) addresses simulation or prediction tasks. These can be considered "classical" forward-looking tasks. For instance, Chapela-Campa and Dumas [10] refer to them as *predictive process analytics*, representing the first layer of capabilities beyond purely descriptive analysis. Historically, simulation and prediction have been addressed by BPS or PPM in isolation, as they do not inherently require technical integration. Thus, the fact that both techniques are used together for these tasks suggests that integration is currently primarily used to improve the accuracy of models rather than to redefine the scope of analysis.

In contrast, only 16% of the papers address tasks beyond simulation or prediction, namely prescriptive process monitoring. Chapela-Campa and Dumas [10] position these capabilities in the augmented BPM pyramid as *prescriptive process optimization*. Unlike prediction, which estimates future outcomes, prescription requires evaluating the effects of alternative behaviors to determine the optimal course of action. Addressing prescriptive tasks, therefore, creates a stronger need to integrate BPS and PPM, as it combines PPM's predictive capabilities and BPS's counterfactual reasoning capabilities.

4.3 RQ2: BPS and PPM Integration Pattern

To answer RQ2, we analyze the conceptual integration between BPS and PPM by examining the roles the two techniques play in it. In the following, we first present the integration patterns we used to categorize the different roles, present the frequencies of their occurrences, and then discuss the related findings.

Introduction of integration patterns. To categorize how simulation and prediction are combined, we defined seven integration patterns describing how BPS and PPM can be integrated. These patterns abstract from implementation details and instead capture the functional dependency between the two techniques. As shown in Figure 3, we distinguish between asymmetric and symmetric integration patterns. In asymmetric patterns, one technique acts as the primary technique (client) and leverages the other as a supporting component (server) [22]. When BPS acts as the client, predictive models may (P1) provide input to the simulation model, (P2) be embedded as an intermediate component within the simulation workflow, or (P3) be applied to simulation outputs. Conversely, when PPM acts as the client, simulation may (P4) generate input for predictive models,

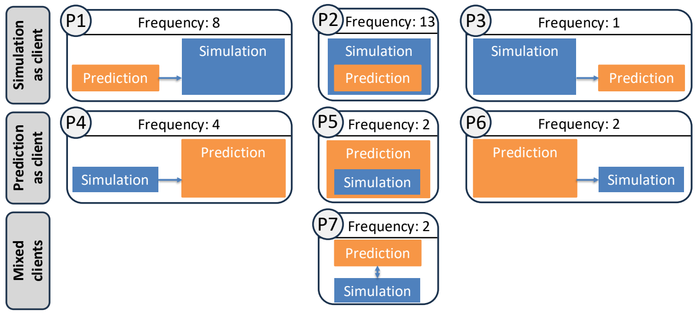

Fig. 3: Integration patterns and their observed frequencies.

(P5) be integrated as an intermediate component within the predictive pipeline, or (P6) be applied to prediction outcomes. Finally, pattern (P7) captures symmetric integration, in which BPS and PPM are tightly coupled and jointly contribute to forward-looking analysis without a clear client–server relationship.

Observed frequencies of integration patterns. Figure 3 summarizes the frequencies of the identified integration patterns. The results show a clear predominance of simulation-centered integrations. 22 papers use BPS as the primary client technique. In these cases, prediction either provides input to the simulation (P1) [6, 9, 19, 20, 25, 28, 45, 53] or is embedded within the simulation workflow (P2) [4,5,7,18,23,31,32,35,37,40,48,55,56]. Only one paper uses simulated outputs as input to a PPM model (P3) [41]. Among the eight papers where prediction acts as the client technique, the distribution across patterns is more balanced: four follow P4 [11, 36, 42, 51], two follow P5 [49, 57], and two follow P6 [12, 13].

In addition to the predominantly asymmetric patterns, two papers implement the symmetric pattern P7, where neither technique assumes a clear client role. In the first work, symmetry arises because alternative methods for predicting process performance are proposed in which the ordering of simulation and prediction models varies across configurations [52]. In the second work, a unified environment supporting both simulation execution and performance prediction is proposed [43].

Discussion. Overall, the identified integration patterns exhibit a clear, albeit not strict, alignment with the tasks discussed in Section 4.2. Papers addressing simulation tasks predominantly adopt patterns P1–P3, in which simulation acts as the client technique and prediction provides input or is embedded in the simulation. Similarly, papers that address prediction tasks mainly follow patterns P4 and P5, in which prediction is the client technique and simulation acts as a supporting server. The only exceptions to these are the two papers following P7. Papers addressing prescriptive tasks, in contrast, consistently adopt prediction as the client technique, but employ different integration patterns (P4–P6). This suggests that multiple integration strategies are explored for prescriptive tasks.

Yet, overall, predictive models are most often used to parameterize or refine simulation models, predicting the future behavior of running instances, and generating event data across different process perspectives. The most common application of these generative models is the prediction of temporal dynamics, such as processing and waiting times (e.g., [6,35]). They are used less frequently to generate activity sequences [5,31] or to predict resource-related behavior [28,36]. Only a few approaches generate event data attributes [5,32]. A detailed overview of the process perspectives covered in prior work is provided in our supplementary GitHub repository. Notably, recent approaches increasingly generate multiple perspectives jointly (e.g., [5,23,56]). For example, CoSMo [40] uses a predictive model to generate next activities and remaining time while declarative constraints guide the generation process. The growing use of generative models reflects the need to capture complex, multi-dimensional dependencies in event logs that cannot be adequately represented by simple probability distributions.

4.4 RQ3: Synergies from Integrating BPS and PPM

Beyond tasks and integration patterns, we analyze which concrete synergies arise when BPS and PPM are combined. While RQ1 addresses *what* is studied, and RQ2 *how* both techniques are integrated, RQ3 focuses on *what* is achieved through the integration.

Observed synergies. We identified the following six synergies:

- S1: Simulation is used to generate synthetic data to train and validate predictive models.
- S2: PPM flags risky cases at runtime, and simulation runs micro-what-ifs for prescriptive support.
- S3: PPM-based drift detection feeds back to update simulation parameters.
- S4: PPM is used to determine parameters of the simulation model.
- S5: Simulation is used to assess the impact or usefulness of prediction or forecasting accuracy.
- S6: PPM is used to evaluate BPS models.

Table 1 summarizes the frequency of these synergies. Since a paper may exhibit more than one synergy, the total exceeds 32. The dominant synergy is S4, i.e., the use of PPM to determine simulation parameters. S5 is the second most common synergy, while the remaining synergies occur only occasionally.

Discussion. Table 1 relates the identified synergies to the integration patterns from Section 4.3. Overall, the results reinforce the picture of a predominantly simulation-oriented integration. In particular, S4 occurs almost exclusively in P1 and P2, showing that predictive models are mainly used to parameterize simulation models either upfront (P1) or dynamically during execution (P2). This confirms that the most established role of PPM in the reviewed literature is to make simulation models more data-driven and adaptive.

S5 shows a broader distribution across patterns. It appears not only in prediction-oriented settings (P4–P6), where simulation is used to assess the usefulness of predictive results, but also once in P1 [25]. This suggests that simulation is occasionally used not only as a target of predictive enhancement but also as a means to evaluate the value of predictive accuracy.

S1 is likewise distributed across several patterns, indicating that simulation can support predictive models in different ways, particularly through synthetic

Table 1: Co-occurrence of Synergies and Integration Patterns

	Integration Pattern							
Synergy	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**Sum**
S1				2		1	1	**4**
S2	1				2			**3**
S3		2						**2**
S4	7	13					1	**21**
S5	1			2	1	2		**6**
S6			1					**1**

data generation for training or validation. By contrast, the remaining synergies are rare and occur only in specific settings: S2 appears in a small number of prescriptive, runtime-coupled scenarios, S3 occurs only in P2, and S6 appears only once [41], where predictive techniques are used to assess the utility of the simulation model rather than to support the execution of the simulation itself. Overall, the synergy analysis shows that, although several forms of interplay between BPS and PPM exist, the literature is clearly dominated by the use of predictive models to improve simulation.

4.5 Synthesis of Main Findings

Taken together, the results suggest that the current integration of BPS and PPM is characterized by three main features. First, integration is predominantly *asymmetric*, meaning that one technique usually acts as the client while the other provides supportive functionality. Second, this asymmetry is strongly simulation-oriented: most studies use PPM to parameterize, refine, or dynamically update simulation models, rather than the other way around. Third, the most advanced use of combining BPS and PPM appears in prescriptive settings, by means of, e.g., recommending interventions. While the majority of papers still focus on classical tasks such as simulation and prediction, prescriptive studies reveal the strongest complementarity between both techniques, since they require both forecasting future developments and assessing the consequences of alternative interventions. Overall, the literature points to a growing but still narrow integration landscape in which PPM primarily serves to enhance BPS.

5 Future Research

While existing work demonstrates the potential of combining BPS and PPM, the findings above reveal several open research directions that warrant further investigation. We first discuss how tighter integration may help address known challenges of both BPS and PPM in Section 5.1. We then outline broader research directions towards more decision-oriented forms of integrated forward-looking process analysis in Section 5.2.

5.1 Overcoming Known Challenges

Previous works have identified critical challenges of BPS and PPM, respectively. We discuss how the integration of the two may help to tackle these challenges, providing a basis for future work.

PPM to tackle challenges in BPS. Following Dumas [15], we recognize two main challenges of BPS and explain how PPM can address them.

1. **Modeling human behavioral variability:** A persistent challenge in BPS is the realistic representation of human behavior. Simulation models often treat human resources in a simplified and overly deterministic manner, thereby failing to capture individual differences, temporal fluctuations in performance, or context-dependent decision behavior. This is particularly problematic in knowledge-intensive and service-oriented processes, where human choices strongly shape process outcomes. While agent-based simulation (ABS) provides a more flexible basis for representing autonomous and interacting resources than traditional DES [27, 28], specifying realistic agent behavior remains difficult. A promising direction for future research is therefore to integrate PPM models into ABS-based BPS. Predictive models trained on event logs can learn context-sensitive patterns of human behavior—for example, how routing choices, execution times, or escalation decisions depend on workload, case characteristics, or recent process history—and use these patterns to inform agent decisions. In this way, PPM can help move BPS from static behavioral assumptions toward data-driven and adaptive models of human behavior.
2. **Modeling intervention effects on process performance:** A further challenge in BPS is to estimate realistically how process performance changes after interventions. This is particularly difficult for structural interventions, as current BPS models are often calibrated in a frequentist manner, i.e., simulation parameters are estimated from historical executions and then reused to simulate future behavior. While this can be adequate for simple interventions with localized effects, it becomes problematic when interventions alter the contextual factors that shape process behavior. In such cases, the assumption that pre-intervention distributions remain valid after the intervention may no longer hold. A promising direction for future research is therefore to complement such aggregate, history-based models with context-sensitive predictive components from PPM. Predictive models can learn how process behavior depends on case attributes, workload conditions, resource constellations, or decision rules, and use this information to make simulation behavior more context-aware. PPM cannot eliminate the fundamental uncertainty of unprecedented interventions, but it can help BPS move from static aggregate assumptions toward context-aware approximations of behavioral change.

BPS to tackle challenges in PPM. Following Ceravolo et al. [8], we recognize three main challenges of PPM and explain how BPS can address them.

1. **Human interpretability and trust:** A first promising direction is to use BPS to improve *human-centered PPM*. While recent PPM research increasingly relies on deep learning models, their predictions are often difficult to interpret and therefore hard to trust in operational settings. Future work should investigate whether simulation can serve as an explanatory layer around predictive models. Instead of presenting predictions in isolation, integrated systems could embed them into simulated future execution scenarios that illustrate *why* a certain risk, delay, or outcome is predicted and how this prediction depends on specific process conditions. Such scenario-based explanations may be easier for process participants to understand than opaque model outputs alone. More generally, simulation could be used to translate black-box predictions into actionable narratives by showing plausible future paths, resource constellations, bottlenecks, or intervention effects. This would shift explanation in PPM from a purely feature-based perspective toward a process-aware and decision-oriented form of interpretability.
2. **Model autonomy and standardization:** A second research direction concerns *model autonomy and standardization*. A major bottlenecks in PPM is the high effort required for data preparation, model adaptation, and benchmarking under changing process conditions. Here, BPS offers a controlled environment for automated data generation, systematic variation, and reproducible evaluation. Future work should therefore investigate simulation-based pipelines that automatically generate labeled event logs for training and tuning predictive models, including under rare but operationally important scenarios that are often underrepresented in real data. In addition, simulation can provide standardized concept-drift scenarios by varying routing logic, arrival rates, or resource availability. This would enable more rigorous development and evaluation of adaptive PPM approaches. Closely related, integrated BPS–PPM environments could serve as benchmark generators that provide reproducible evaluation settings with known ground truth, thereby helping to address the lack of standardized datasets and evaluation protocols in PPM.
3. **Practical relevance of PPM:** A third research direction is to leverage BPS to increase the *industry impact* of PPM. One reason why PPM remains difficult to translate into practice is that several established prediction tasks are not inherently decision-critical. Except for notable cases such as remaining-time prediction, which can directly support delay management and resource allocation, many common PPM tasks provide information that is interesting from a modeling perspective but only weakly connected to concrete operational decisions. Future research should therefore move beyond stand-alone prediction tasks and investigate how BPS can make PPM outputs actionable. In particular, predictive signals from ongoing cases could be coupled with simulation-based analysis of alternative interventions, allowing organizations to evaluate not only what is likely to happen, but also which actions are likely to improve outcomes. This would reposition PPM from a forecasting tool toward a component of decision-oriented process steering.

5.2 Towards Decision-Oriented Forward-Looking Analysis

We outline three directions for future research that go beyond addressing known challenges. These directions can be understood as a progression from (1) understanding and acting upon requirements through real-life use cases, (2) strengthening decision support, and (3) moving towards fully integrated digital process twins.

1. Adopt a use case perspective. Future research should more strongly adopt a practical use-case perspective when developing and integrating BPS and PPM. Our review shows that, although some studies are motivated by concrete application scenarios, much of the literature remains centered on generic prediction and simulation tasks, with integration often serving mainly to improve model accuracy. As a result, it remains unclear which forms of integration are needed in practice and which tasks create meaningful decision support in real organizational settings. A promising next step is therefore to start from concrete decision situations and practitioner requirements, rather than from available modeling techniques alone. This includes systematically studying use cases from both the literature and industry to identify common shortcomings in current approaches, determine whether decisions require predictive capabilities or simulation-based reasoning, and assess where combining both adds value. Such a perspective can help distinguish practically relevant forms of integration from technically feasible but low-impact ones, providing a stronger foundation for future methodological work. Independent of the outcome of these analyses, some aspects are consistently relevant. In particular, evaluation should be treated as a first-class concern: prescriptive approaches and integrated systems can only provide value if their recommendations are reliable. This is difficult because prescriptive recommendations are counterfactual, online tests may be infeasible, simulation-based evaluation can be biased, and decision quality depends on feasibility and delayed system-wide effects. This calls for further systematic evaluation strategies to assess the quality and impact of decisions enabled by integrated BPS–PPM approaches.

2. Towards more decision support. The primary motivation for forward-looking process analysis is decision support. However, the results of this review indicate that current integrations of BPS and PPM are primarily designed to provide information rather than offer real guidance in this support. Future research should therefore focus on decision-centric integration strategies for operational and strategic decisions such as prioritization, escalation, resource assignment, staffing, or scheduling. A promising direction is to combine PPM and BPS in closed decision loops: PPM detects critical future developments in ongoing cases, while BPS evaluates alternative interventions before deployment. For instance, if a model predicts a high delay risk, simulation can assess whether rerouting work, reallocating resources, or changing priorities would improve outcomes. Such loops require careful alignment between PPM and BPS models, which may differ in granularity, assumptions, learning mechanisms, and objectives, potentially leading to inconsistent or self-reinforcing decisions. Beyond case-level interventions, future work should also investigate integration with optimization approaches to support process-level decisions such as capacity planning and scheduling. In this way, integrated BPS–PPM can move from forecasting future behavior toward recommending actions that improve process performance.

3. Towards adaptive digital process twins. Digital (process) twins, and—at a broader organizational level—digital twins of an organization, represent the most comprehensive integration of predictive and simulation capabilities in BPM. Although frequently described as a long-term vision for forward-looking analysis [1, 10, 16, 21], the reviewed literature shows that existing approaches remain largely offline and loosely coupled, with only limited feedback between BPS and PPM. Future research should therefore investigate tightly coupled architectures in which predictive and simulation models continuously inform each other. Such systems require mechanisms for incremental model updating based on event streams, enabling both predictive models and simulation parameters to adapt to evolving process behavior. In this context, handling concept drift becomes a central challenge for maintaining model validity over time. Beyond concept drift, adaptive twins must synchronize evolving models, distinguish meaningful change from noise, and maintain uncertainty and traceability. Furthermore, human-in-the-loop mechanisms are a promising approach for guiding model updates and intervention decisions, ensuring that such systems remain reliable and aligned with operational objectives.

6 Conclusion

In this work, we conducted a structured literature review on the integration of business process simulation (BPS) and predictive process monitoring (PPM). Based on 32 studies, we analyzed which tasks are addressed, how both techniques are integrated, and which synergies arise. Overall, the literature shows a growing but still narrow integration landscape: existing approaches are predominantly asymmetric and simulation-oriented, with PPM mainly used to parameterize or refine BPS. At the same time, the reviewed prescriptive approaches indicate that the strongest existing complementarity of BPS and PPM emerges when forecasting ongoing executions is combined with simulation-based assessment of alternative interventions. On this basis, we outlined future research directions for advancing integrated forward-looking process analysis from loose, simulation-centric coupling toward adaptive and decision-oriented support in business processes.

This review is subject to several threats to validity. First, despite searching multiple digital libraries and applying backward and forward snowballing, coverage bias may arise from the chosen search terms, databases, and inclusion criteria, such that relevant studies may have been missed. Second, interpretation bias may affect the coding of tasks, integration patterns, and synergies, since these classifications involve subjective judgment. We mitigated this threat through iterative refinement of the coding scheme and discussion of ambiguous cases among the authors. Despite these limitations, we believe that this work provides a strong foundation for future research on forward-looking process analysis.

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