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Review

Towards integrating process mining with agent-based modeling and simulation: State of the art and outlook

Rob H. Bemthuis [a,*], Sanja Lazarova-Molnar [b,c]

[a] Pervasive Systems, University of Twente, Drienerlolaan 5, Enschede, 7522 NB, The Netherlands
[b] Institute of Applied Informatics and Formal Description Methods, Karlsruhe Institute of Technology, Kaiserstr. 89, Karlsruhe 76133, Germany
[c] Mærsk Mc-Kinney Møller Institute, University of Southern Denmark, Campusvej 55, Odense 5230, Denmark

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ABSTRACT

Agent-based modeling and simulation (ABMS) is a valuable tool for assessing complex socio-technical systems and is becoming increasingly advanced through the integration with data-driven capabilities. Process mining is an emerging data-driven discipline that combines elements from data mining and process modeling to gain insights into process execution through tasks such as process discovery, conformance checking, and process enhancement using event data. This study explores the role of process mining and its impact on the ABMS paradigm, identifying the current state of the art, gaps in the literature, and future directions for integrating process mining with ABMS. A systematic literature review is conducted to examine how ABMS and process mining techniques are jointly employed to address challenges reported in the literature. From an initial pool of 189 publications, a final set of 20 papers was synthesized, their primary contributions were discussed, and open issues and challenges for future research were identified. Although the integrated field of process mining and ABMS shows an upward trend in publications, it remains modest and requires further efforts to achieve synergistic improvements in socio-technical systems. The findings offer initial guidance for promising research directions.

Contents

* Corresponding author.
E-mail addresses: r.h.bemthuis@utwente.nl (R.H. Bemthuis), slmo@mmmi.sdu.dk, lazarova-molnar@kit.edu (S. Lazarova-Molnar).

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1. Introduction

Future generations of modeling and simulation techniques must evolve to handle the anticipated influx of big data (Kim & Kim, 2020; Ullah, 2019). Consequently, current modeling and simulation efforts are becoming more advanced, closely mimicking real-life socio-technical systems that are adaptable to future advancements (Hansen, Liu, & Morrison, 2019). New approaches that integrate data-driven techniques with modeling and simulation are shaping a range of complex and dynamic systems.

This study investigates the use of process mining as a data-driven technique in combination with agent-based modeling and simulation (ABMS). ABMS has proven effective in various applied disciplines and domains as a modeling and simulation approach to understand complex systems (Baqueiro, Wang, McBurney, & Coenen, 2009; Castiglione, 2020; Macal & North, 2014). As the use of ABMS in research and practice has grown (e.g., Abar, Theodoropoulos, Lemarinier, & O'Hare, 2017; DeAngelis & Diaz, 2019; Hansen et al., 2019; Heath, Hill, & Ciarallo, 2009; Khodabandelu & Park, 2021; Onggo & Foramitti, 2021; Utomo, Onggo, & Eldridge, 2018), the integration of data-driven capabilities in ABMS has also increased (e.g., Charalambous, Pettre, Vassiliades, Chrysanthou, & Pelechano, 2023; Collins, Koehler, & Lynch, 2024; Platas-López, Guerra-Hernández, Quiroz-Castellanos, & Cruz-Ramirez, 2025). This integration facilitates the exploration of how individual-level behaviors and interactions lead to observable system-level patterns. Process mining is one such data-driven technique. It encompasses a broad range of techniques and analysis methods based on event logs to extract information about processes (van der Aalst, 2011).

Applications and case studies explore the intersections between ABMS and process mining (Sulis & Taveter, 2022). In typical agent-based systems, macro-level behaviors become increasingly complex over time, even though the complexities of individual agents remain constant or nearly so, often due to simple governing rules (Tour, Polyvyanyy, & Kalenkova, 2021). Agents can encapsulate the relationships among generated process models, process insights, and runtime behaviors within a model. Therefore, the ABMS paradigm has the potential to intrinsically cope with the increasing complexity of process mining techniques, such as the complex process models discovered (e.g., "Lasagna" or "Spaghetti" processes). Other directions include generating and verifying agent-based models based on process mining (e.g., Ou-Yang & Juan, 2010), as well as analyzing existing agent-based systems using process mining techniques (Jimenez, Zambrano-Rey, Aguirre, & Trentesaux, 2018). Another application involves enabling agents to utilize process mining techniques in their decision-making processes (Bemthuis, Mes, Iacob, & Havinga, 2020). Thus, process mining can be applied to address challenges in ABMS and vice versa, and both can be used to tackle problems.

In this paper, we provide a review of the state of the art of using process mining in conjunction with ABMS, discuss the main open issues and challenges currently reported in the literature, and suggest future research directions. To this end, we begin by conducting a systematic literature review. A systematic literature review is a methodical approach to identify, evaluate, and interpret the available studies conducted on a topic, research question, or phenomenon of interest (Kitchenham, 2004). We selected this method to minimize researchers' bias by adhering to a predefined review protocol.

The motivation for this literature review stems from the growing popularity of combining process mining with ABMS (Tour et al., 2021), while recent applications and advancements of process mining in other domains indicate its significant potential (dos Santos Garcia et al., 2019; Maita et al., 2018). Current literature reviews on process mining (e.g., Dakic, Stefanovic, Lolic, Narandzic, & Simeunovic, 2019; Sato, De Freitas, Barddal, & Scalabrin, 2021; van Zelst, Mannhardt, de Leoni, & Koschmider, 2021) mostly cover theoretical aspects (e.g., concept drift, event log extraction, etc.) or focus specific domains such as healthcare (e.g., De Roock & Martin, 2022; Kusuma, Hall, Gale, & Johnson, 2018) or education (e.g., Bogarín, Cerezo, & Romero, 2018). Similarly, survey papers on ABMS address particular application domains such as transportation (e.g., Jing, Hu, Zhan, Chen, & Shi, 2020; Mualla et al., 2019) or discuss fundamentals and tools (e.g., Abar et al., 2017; Brailsford, Eldabi, Kunc, Mustafee, & Osorio, 2019; de Paula Ferreira, Armellini, & De Santa-Eulalia, 2020; Gao et al., 2024). In a literature review examining work related to both ABMS and process mining, Tour et al. (2021) provided an overview of results and gaps in the existing knowledge base. However, their scope is broader, focusing on business process management (BPM) and data mining in general. Furthermore, they mainly address related work pertinent to their envisioned framework, whereas in this article, we delve deeper into the relationships between ABMS and process mining. Although earlier work has introduced the integration of data mining and ABMS (Baqueiro et al., 2009), to our knowledge, no review has addressed studies on process mining in conjunction with ABMS. Moreover, unlike Baqueiro et al. (2009) and Tour et al. (2021), we also provide a future outlook. By focusing on ABMS and process mining, we offer a complementary perspective to the recent studies by providing a more in-depth analysis of ABMS and process mining as a unified topic.

The key contributions of this paper are as follows:

- A systematic review of the current state-of-the-art concerning ABMS in conjunction with process mining is provided;
- Open issues and challenges in this joint field are identified and explored;
- Potential future research directions are suggested based on the existing limitations and challenges of the combined ABMS and process mining fields.

The remainder of the paper is organized as follows. Section 2 discusses the background. Section 3 details the systematic literature review conducted. Section 4 presents our findings. Section 5 highlights future research directions. Finally, Section 6 concludes our work and discusses further implications.

2. Background

This section first provides background of ABMS, followed by the topic of process mining.

2.1. Agent-based modeling and simulation

ABMS refers to a general modeling and simulation paradigm, where agent-based modeling involves creating a model, and agent-based simulation is the process of executing the model (Klügl & Bazzan, 2012). In ABMS, the primary modeling construct is an agent and its associated behaviors, which influence not only the agent's own actions but also those of other agents and the environment (Macal, 2016). Each agent operates within an environment and interacts with other agents. An agent uses its perception of the environment and its objectives to make decisions, which manifest as actions such as direct interventions, communication with other agents, or further reasoning.

In an agent-based model, system-level (macro) behavior emerges from the (micro) behavior of individual agents, which can be entities such as persons, cells, or any other discrete quantities (Bodine, Panoff, Voit, & Weisstein, 2020). A typical agent-based model contains at least three components: agents, an environment, and rules. The behavior of each agent is governed by rules related to its interactions with other agents and the environment (Bonabeau, 2002; Taveter & Wagner, 2001). Agent-based modeling often focuses on examining the emergent macro-level system performance.

Although agent-based simulation can be perceived as a special form of discrete-event simulation (Law, 2015), there is an ongoing debate about whether ABMS can incorporate all elements of discrete-event simulation and vice versa (Macal, 2016). This debate is beyond the scope of this study; instead, the assumption is made that the ABMS paradigm is suitable for applying process mining and vice versa (e.g., through the notion of event logs). This assumption is supported by the fact that agents, due to the bottom-up modeling approach, can inherently handle the complexities arising from data analytics techniques such as process mining (e.g., producing or analyzing event logs, and executing data analytics methods). Furthermore, as discussed later (in Sections 3 and 4) and as initial insights have shown by Tour et al. (2021), there are numerous and diverse use cases that indicate the potential synergy between these disciplines.

2.2. Process mining

Fig. 1 provides an overview of how process mining establishes links between real-world processes and data, and process models. Software systems, including agent-based systems, can generate massive amounts of data. Process mining utilizes details about the executed activities in the form of event logs (van der Aalst, 2011). These digital traces can be distributed across multiple systems and may exist in various forms.

Three types of process mining techniques can be distinguished (see Fig. 1). Process discovery produces a model without using any a priori information (van der Aalst, 2011). The input is an event log, and the output is a model. Typically, the model is a process model (e.g., a Petri-net or BPMN), but it may also produce other models such as a social network. Conformance checking compares the "reality" recorded in the log to a model and vice versa (van der Aalst, 2011). The input concerns an event log and a process model, and the output consists of diagnostic conformance details. Enhancement extends or improves an existing process model using the event logs (van der Aalst, 2011). The input consists of an event log and a model, while the output is an improved or extended model.

An event log is a collection of historical records from process instances (van der Aalst, 2011). Process mining techniques rely on the existence of an event log that sequentially records events, where each event refers to an activity (i.e., a well-defined step) and is related to a particular case (i.e., process instance). A trace corresponds to a sequence of events produced during the execution of a process instance, and an event log contains the set of all such traces. Additional information about events, such as the affiliated resource (e.g., person, organization, and device), timestamp, or other data elements, can also be stored in an event log (van der Aalst, 2016).

To conduct process mining analysis, every activity should be ordered, for instance, using a timestamp. This requirement also applies to event logs in system dynamics, where a distinction can be made between event logs and process logs—the latter representing measurable aspects derived from event logs (Pourbafrani & van der Aalst, 2022). In the context of agent-based systems, this distinction extends further to event logs and agent logs. Agent log files, produced by individual agents, can reflect different discretizations of step ordering, depending on whether the steps represent specific events or time-based intervals. These log files, which can be referred to as agent log files, can be used for designing, generating, and analyzing agent-based models and systems.

Unlike other modeling and simulation techniques that usually start from modeled behavior, process mining generally starts from observed behavior (Măruşter & van Beest, 2009; van der Aalst, 2016). For example, process mining can capture complex processes that were previously simplified out of the model (Greasley & Edwards, 2021). Additionally, process mining can complement other stages of modeling and simulation methodologies, such as input modeling, model building, and experimentation (Greasley & Edwards, 2021; Keith Norambuena, 2018). Process mining be applied to agent-based systems to generate accurate models based on real-time, fine-grained data, useful for verification or validation purposes. Conversely, process mining can also benefit from techniques developed within the ABMS paradigm (Halaška & Šperka, 2018; Tour et al., 2021).

3. Methodology

This study follows the methodology outlined by Kitchenham (2004) and Kitchenham et al. (2009) to conduct the literature review. This approach offers clear guidance, practical steps, and is widely adopted by researchers in the field. The following outlines the key aspects of the methodology, including the research questions, review process, and data synthesis.

3.1. Research questions

The research goal is refined into two research questions (RQs). The first one (RQ1) is: *What is the state of the art of process mining when utilized in conjunction with ABMS?* Our objective is to identify and discuss available evidence regarding the use of process mining alongside ABMS. This includes indicators that a proposed artifact-such as an approach, methodology, or theory-effectively addresses the problem at hand. Beyond identifying existing research, we aim to uncover gaps in current knowledge, including unresolved issues and challenges. This leads us to the second research question (RQ2): *What are the current challenges and future research directions for process mining in conjunction with ABMS?*

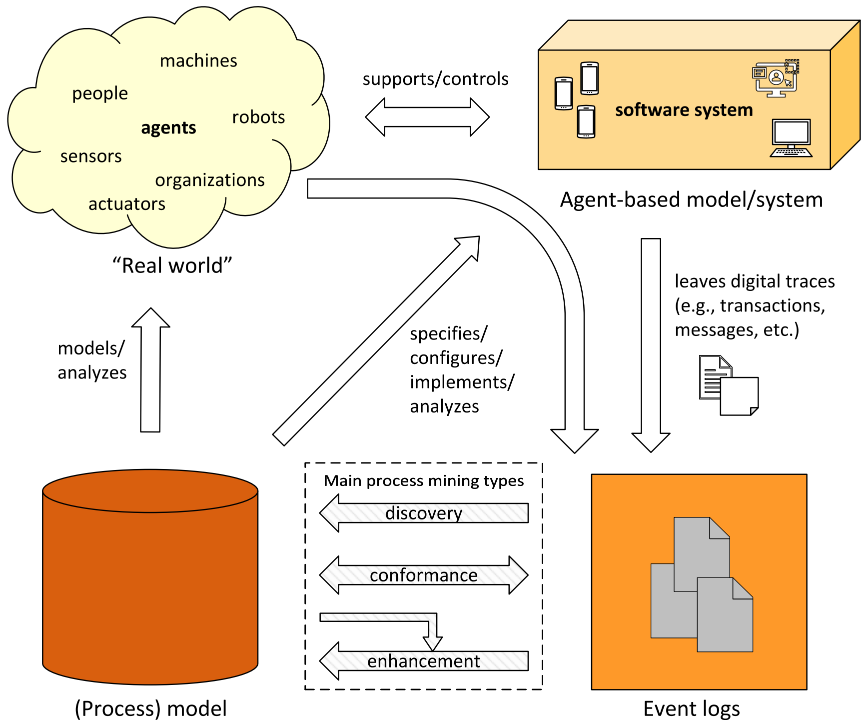

Fig. 1. Process mining in an ABMS context.
Source: adapted from van der Aalst (2011).

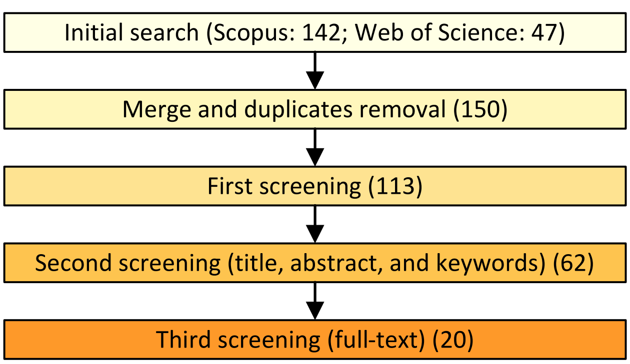

Fig. 2. Overview of literature search and selection process.

3.2. Review methodology

Fig. 2 illustrates our search and selection process across the various stages. Initially, we searched the electronic databases Scopus and Web of Science, which are widely used indexing systems. We used the search string: ("process mining" AND "agent*"). This search yielded 142 papers from Scopus and 47 papers from Web of Science as of July 18th, 2022. After merging and removing duplicates, we had a total of 150 papers.

We then screened the papers based on the following exclusion criteria (EC):

- **EC1**: Papers not written in English.
- **EC2**: Papers not available as full text.
- **EC3**: Short contributions such as editorials or doctoral consortium papers.

This screening process resulted in 113 included papers.

Next, we examined the title, abstract, and keywords based on the inclusion criteria (IC):

- **IC1**: Papers that mention process mining solutions, methods, or techniques.
- **IC2**: Papers that mention agent technology solutions, methods, or techniques.

For IC2, we explicitly looked for the inclusion of the agent construct, rather than general concepts like "person" or "object". In case of doubt, we did not reject the paper at this stage.

We then performed a full-text reading of the 62 resultant papers and reassessed them based on the inclusion and exclusions criteria. Additionally, we applied supplementary criteria:

- **EC4**: Exclude papers that used process mining or agent technology merely as examples, not as research focuses.
- **EC5**: When similar papers existed (e.g., a conference paper expanded into a journal paper), we selected the most comprehensive version.

Again, in cases of doubts, we retained the paper at this stage.

Finally, we assessed the methodological quality of the 62 papers using common literature review quality criteria as mentioned by Yang et al. (2021):

- **Reporting**: The study's rationale, aims, and context.
- **Rigor**: The research methods employed to establish validity.
- **Credibility**: The reliability in ensuring valid and meaningful findings.
- **Relevance**: The value to academia and industry.

Each paper was scored as sufficient or insufficient for each criterion. Only papers that scored at least two "sufficient" ratings were included, resulting in a final selection of 20 articles.

3.3. Data synthesis

We summarized the extracted data to understand and analyze current research on process mining in conjunction with ABMS. Fig. 3 shows

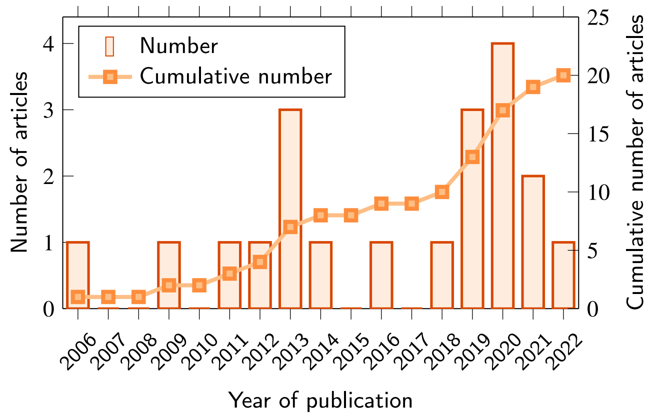

Fig. 3. Number of published articles per year.

the distribution of selected articles per year. Although the number of publications is increasing, it remains a relatively modest research area. We conducted a further analysis to identify common themes and open issues. We used a combination of content analysis and narrative synthesis, detailed in the findings.

4. Findings

This section first presents a classification of the extracted papers on process mining and ABMS, followed by a discussion on the application domains. Lastly, we provide an outlook on notable new findings from studies conducted after the cutoff date of our sample set obtained through the systematic literature review.

4.1. Classification based on interaction between process mining and agent-based modeling and simulation

Combining process mining and ABMS offers numerous possibilities, and the appropriate design greatly depends on the problem characteristics. Inspired by the work of Figueira and Almada-Lobo (2014) on simulation optimization methods, we defined six categories for how process mining can be combined with ABMS (illustrated in Fig. 4):

- **Type I**: Process mining with nested ABMS-based iterations. This involves performing one or more (complete) ABMS-based iterations (like simulation runs) in all (or part) of the iterations of a process mining method. The goal is to achieve a process mining objective while utilizing supportive ABMS techniques. For example, agents might collect and prepare event logs or help fine-tune process discovery algorithm parameters;
- **Type II**: ABMS with nested process mining-based iterations. Here, one or more (complete) process mining procedures are performed in all or part of the iterations of an ABMS artifact. The aim is to achieve an ABMS goal by embedding process mining techniques. An example is an agent-based simulation model where agents use knowledge obtained through process mining discovery techniques;
- **Type III**: Alternating process mining and ABMS. This involves sequentially progressing both modules, with each iteration involving the complete or partial execution of both. The ABMS process and the process mining procedure are mutually interdependent and can be invoked repeatedly. For instance, using the output of an agent-based simulation as input for process mining, which then identifies bottlenecks to guide the next simulation run. This iterative approach can be useful in evaluating multiple scenarios successively (e.g., periodically, such as daily);
- **Type IV**: Process mining followed by ABMS. The aim is to use output produced by process mining for ABMS purposes;
- **Type V**: ABMS followed by process mining. The aim is to use output produced by ABMS for process mining purposes;
- **Type VI**: Complex interactions between process mining and ABMS. This category includes modes of interaction that do not neatly fit into the other categories. These interactions require detailed explanations to clarify how process mining and ABMS are integrated.

The goals, artifacts produced (such as models or methodologies), and validation methods used in the selected papers were examined. The type of interaction was identified based on the categorization presented in Fig. 4. Although some papers address multiple interaction types — for instance, Type III could be viewed as a combination of Types IV and V — the primary contribution of each article was the focus. Conformance checking and enhancement techniques were treated as standalone procedures unless the article's contribution deviated from standard practices.

Table 1 presents the classification of papers. Use cases were found for all interaction types except Type I, which may be attributed to the relative youth of the process mining field. Specialized applications incorporating nested agent technologies require expertise from both areas. The majority of publications (65%) fell under Type V, with fewer articles under Types II or III. Early adaptors primarily applied process mining techniques to output from ABMS artifacts, with less evidence for other interaction types. Some articles address a single interaction type, while many cover multiple types—especially those under Type VI. Below, each paper is discussed in detail, beginning with those that fall under a single classification type, followed by those addressing multiple types.

4.1.1. Type II - ABMS with nested process mining iterations

Hajer et al. (2020) provide a detailed description of the data preprocessing steps needed to transform unstructured event logs into well-structured logs. They propose an agent-based modeling approach using a general multi-agent system (MAS) system architecture. The final two layers of their four-layered architecture focus on process discovery and recommendation, with process discovery nested within the MAS architecture.

4.1.2. Type III - alternating process mining and ABMS

Szimanski et al. (2013) propose an iterative approach to enhance business process models using process mining and agent-based simulation. Process mining captures both the high-level abstraction of modeled processes and the low-level behavior observed through events. Agent-based simulation generates low-level behavior for new process versions. Users can iteratively modify the process model, reconfigure simulations, generate new event logs, and mine a new hierarchical model that links high-level activities to low-level behavior (Szimanski et al., 2013). While their improvement cycle includes elements from Types IV and Type V, their main contribution is the alternation between process mining procedures and ABMS methods (Type III).

Bemthuis et al. (2020) develop an agent-based simulation framework that manages interactions between a cyber–physical system and business logic. The framework uses process mining techniques to discover business processes, and agents learn and incorporate these observations in their decisions. A new agent configuration is then deployed by updating the agents' rules, followed by a newly discovered process model. This process iterates multiple times. The alternating interaction between process mining and ABMS components results in globally observed agent behavior that influences subsequent decisions.

4.1.3. Type IV - process mining followed by ABMS

Augusto et al. (2016) design a methodology to automatically construct an agent-based simulation model using process mining techniques, based on patient clinical pathway data extracted from a hospital

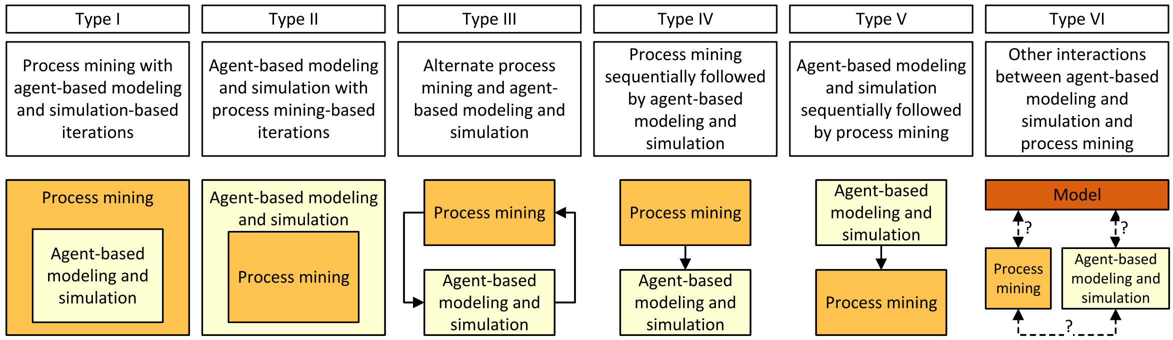

Fig. 4. A classification according to the interaction between process mining and ABMS.

Table 1
Classification of interaction types between process mining and ABMS.

Type	Articles	Number of articles
I	n/a	0
II	Hajer, Arwa, Lobna, and Khaled (2020)	1
III	Bemthuis et al. (2020) and Szimanski, Ralha, Wagner, and Ferreira (2013)	2
IV	Augusto, Xie, Prodel, Jouaneton, and Lamarsalle (2016), Larsen, Burattin, Davis, Hjardem-Hansen, and Villadsen (2019), Nesterov, Bernardinello, Lomazova, and Pomello (2022), Ou-Yang and Winarjo (2011), Polyvyanyy, Su, Lipovetzky, and Sardina (2020), Sohail, Bukhsh, van Keulen, and Krabbe (2021) and Tour et al. (2021)	7
V	Bemthuis et al. (2019), Cabac, Knaak, Moldt, and Rölke (2006), Fauzan, Sarno, and Machfud (2019), Ferreira, Szimanski, and Ralha (2013), Hanachi, Gaaloul, and Mondi (2012), Ito, Vymětal, Šperka, and Halaška (2018), Mecheraoui, Carrasquel, and Lomazova (2020), Nesterov et al. (2022), Ou-Yang and Winarjo (2011), Polyvyanyy et al. (2020), Rozinat, Zickler, Veloso, van der Aalst, and McMillen (2009), Šperka, Spišák, Slaninová, Martinovič, and Dráždilová (2013) and Tour et al. (2021)	13
VI	Nesterov et al. (2022), Ou-Yang and Winarjo (2011), Rozinat et al. (2009), Sonnenberg and Vom Brocke (2014) and Tour et al. (2021)	5

database. The methodology has two main steps. First, process mining techniques produce a causal net, which is then converted into a state chart. Second, an agent-based approach implements the models, associating an agent's decision with the state chart (Augusto et al., 2016).

Larsen et al. (2019) aim to provide insights into the roles within a hospital emergency room. Their approach uses process mining to identify and delineate agents from real-world event logs. They propose steps that start with identifying existing data and lead to an executable agent-based simulation model. A pipeline processes various data types into event logs, which are then used to extract the agent models (Larsen et al., 2019).

Sohail et al. (2021) seek to validate patients' non-anonymized care metadata using process mining discovery techniques. They conceptualize care metadata from a patient's perspective using a Resource-Event-Agent (REA) ontology and discuss privacy concerns. They extract and discuss economic agents, their primary interactions, and collective economic value gains or losses in a socio-technical system.

4.1.4. Type V - ABMS followed by process mining

Cabac et al. (2006) reconstruct models of agent interaction protocols from sample interactions. They apply process mining techniques to analyze, design, and validate multi-agent interactions. They develop a tool to assess agent interaction messages and reconstruct interaction protocols using several process mining techniques (Cabac et al., 2006).

Hanachi et al. (2012) integrate conversations among process performers using a performative-based agent communication language to discover organizational structures. They enrich event logs by incorporating conversations among activity performers, adding agent properties, and creating models depicting these interactions.

Ferreira et al. (2013) determine the relationship between agents' low-level behavior and high-level activities in a process model. They propose a hierarchical Markov model and a procedure to discover the relationship between micro-level events in an event log and macro-level activities in a business process model. Their goal is to model agent's behavior at the micro-level model and fit it into the macro-level process description.

Šperka et al. (2013) conduct MAS simulations without real business data. They design a control loop model using the JADE development platform for MAS implementation. They analyze simulation outputs through process mining to extract sequences of actions performed by agents. This knowledge is used for model verification (Šperka et al., 2013).

Ito et al. (2018) focus on analyzing and interpreting simulation results of a multi-agent model using process mining. They extend a MAS simulator to enable analysis of implemented models via process mining. They formalize an abstract agent-based architecture, define event logs extraction, and import logs into a process mining tool for analysis (Ito et al., 2018).

Bemthuis et al. (2019) propose an approach to analyze and evaluate emergent behaviors from agent-based decision-making using process mining. They present an architecture illustrating the relationship between agent-based modeling and process mining when analyzing emergence from the agent interactions. Agents follow rules, and the resulting macro-level behavior is discovered using process mining discovery techniques. A case study demonstrates system performance under different agent configurations (Bemthuis et al., 2019).

Fauzan et al. (2019) develop a method to generate potential future traces and event logs by using ABMS in the context of multiple organizations communicating asynchronously. They analyze communication patterns and their evolution using process mining (Fauzan et al., 2019). Their agent-based simulation model predicts future event logs for subsequent process mining analysis.

Mecheraoui et al. (2020) propose a compositional approach for conformance checking between nested Petri-nets and event logs of a MAS. Event logs generated in a MAS are decomposed into nested Petri-net projections. They explain how conformance checking can be performed separately between each projection and the corresponding model component.

4.1.5. Type VI - complex interactions between ABMS and process mining

Sonnenberg and Vom Brocke (2014) investigate integrating and structuring accounting data and process data to support business process design, execution, and control. They propose a generalized data structure for event logs based on the REA ontology. The model formalizes the integration of process-aware information systems and accounting systems, focusing on the event data structures. This article is classified as Type VI due to its exploration of the intersection between ABMS and process mining from an REA perspective.

4.1.6. Multiple types

Rozinat et al. (2009) distinguish between analyzing agents within the same team and opposing agents. They use a process discovery algorithm to examine actions of individual agents and agent groups within the same team (Type V). Combining a process discovery algorithm with a machine learning model reveals process models for self-analysis and opponent analysis (Type VI).

Ou-Yang and Winarjo (2011) address the relationship between a MAS development tool and a Petri-net simulator, proposing a framework that supports the construction and analysis of a MAS. For each agent, the system generates event logs and applies process discovery to obtain a Petri-net model (Type V). It then merges these Petri-nets based on incoming and outgoing places between agents' models (Ou-Yang & Winarjo, 2011). Simulation and analysis are conducted on the integrated Petri-net model (Type IV). The framework includes modifying the original MAS based on analysis of the integrated Petri-net (Type IV). This indicates a loop of zero or more iterations of MAS modifications based on process mining results. While this could be seen as alternating between process mining and ABMS (Type III), it is considered as Type VI due to the merging of discovered Petri nets into a new model for MAS modifications and the interaction loop based on process mining results.

Polyvyanyy et al. (2020) discuss probabilistic agent goal recognition by aligning observations with process models. They use process mining techniques to discover models (Type V) that describe observed recorded behaviors and diagnose deviations between the discovered models and observations. Conformance diagnostics help understand an agent's objectives (Type IV). Conformance checking is operationalized by aligning retained models with agent trace fragments.

Tour et al. (2021) combine process mining and agent-based modeling in business process management to infer agent models from real-world event data. They introduce Agent System Mining (ASM) and an ASM framework. ASM combines process mining and agent-based modeling to automatically infer MAS models that encode processes from real-world event data (Type IV). The framework maps ASM activities to ABMS lifecycle phases. ASM algorithms create, analyze, and enhance models that represent real-world agents. These models are developed using existing MASs, business process models, and a mix of real-world and simulated event logs (Tour et al., 2021). The framework attempts to automate simulation and modeling tasks, addressing agent model inference from event logs (Type IV) and applying process mining techniques to MAS outputs (Type V). The framework describes multiple interactions between process mining and ABMS techniques, including activities, artifacts, and model repositories (Type VI).

Nesterov et al. (2022) propose a compositional approach to discover architecture-aware and sound process models from event logs generated by MASs. They filter event logs by actions belonging to each agent, resulting in sub-logs. Agent models are discovered from these sub-logs using existing process mining discovery algorithms (Type V). They check for mappings of agent models to corresponding interface parts using typical interaction patterns. This mapping can be classified as a complex interaction between process mining techniques and ABMS methods (Type VI). They introduce neighboring transitions to estimate how well the discovered process model structure covers agent interaction architecture viewpoints. Their approach addresses reference models, directly discovered models, and compositionally discovered models concerning complex agent interactions, involving deriving agent models from discovered process models (Type IV) and complex interactions (Type VI).

4.2. Process mining techniques

Table 2 shows the main process mining techniques addressed by the extracted articles. We differentiate between conceptual studies presenting preliminary findings requiring further validation and complete studies supported by empirical evidence or case studies. Out of the total number, 16 focus on discovery techniques, 6 on conformance techniques, and 2 on enhancement techniques. Additionally, 4 studies pay particular attention to event logs. Below, we discuss articles presenting preliminary findings and those addressing complete approaches. Our review did not identify any complete studies related to enhancement.

4.2.1. Conceptual discovery, conformance checking, and enhancement techniques

Rozinat et al. (2009) emphasize that the impact of distributed autonomous entities becomes apparent as the process unfolds, and the resulting behavior may not be predictable beforehand. Observe the behavior is necessary to assess its actual impact. In process enhancement, they suggest improving process models by utilizing time information and visualizing specific indicators, like the length of stay, using different colors.

Tour et al. (2021) combine process mining with agent-based modeling to automatically create MASs. They extend process mining to incorporate the ABMS paradigm. They introduce a framework with different phases, activities, and artifacts (as also discussed in Section 4.1). To validate their approach, they provide examples and highlight ASM challenges. In the "develop" phase, process mining discovery and enhancement activities infer agent-sub models, environment sub-models, and interaction sub-models, assembling the MAS model (Tour et al., 2021). Inputs include a metamodel, a model framework, and existing event logs and models. The output is a MAS model with multiple agent sub-models, one environment model, and one interactions model. Conforming checking can be linked to the next phase, called "Evaluate", which verifies and validates input MAS models and sub-models, producing simulated event logs (Tour et al., 2021). Diagnostic activities provide quality indicators for modeled systems, and checking activities identify differences between new model versions, existing verified versions, and real-world or simulated event logs (Tour et al., 2021).

4.2.2. Discovery techniques

We consider the four analysis perspectives of process mining defined by van der Aalst (2016): control-flow (e.g., order of activities), organizational/resource (e.g., structures and people involved), time (e.g., timing, duration, frequency), and case/data (e.g., data elements of individual instances). Table 3 shows the primary perspectives addressed in the selected articles. Many articles (15) focus on the control-flow perspective, while fewer address organizational (5 articles) and time perspective (6 articles). Only one article focuses on the case perspective. Below, we outline the main process mining perspectives considered.

Cabac et al. (2006) reconstruct interaction models from event logs that describe agent interactions. Their approach covers aspects of both control-flow and organizational perspectives. They mine activity sequences from message logs and study communication protocols among agents (Cabac et al., 2006). Rozinat et al. (2009) discover a process

Table 2
Maturity levels of process mining techniques in the reviewed articles.

		Conceptual	Complete
Process mining techniques	Discovery	Tour et al. (2021)	Augusto et al. (2016), Bemthuis et al. (2019, 2020), Cabac et al. (2006), Ferreira et al. (2013), Hanachi et al. (2012), Ito et al. (2018), Larsen et al. (2019), Nesterov et al. (2022), Ou-Yang and Winarjo (2011), Polyvyanyy et al. (2020), Rozinat et al. (2009), Sohail et al. (2021), Šperka et al. (2013) and Szimanski et al. (2013)
	Conformance	Tour et al. (2021)	Bemthuis et al. (2019), Mecheraoui et al. (2020), Nesterov et al. (2022), Rozinat et al. (2009) and Polyvyanyy et al. (2020)
	Enhancement	Rozinat et al. (2009) and Tour et al. (2021)	n/a
Other	Event logs	n/a	Fauzan et al. (2019), Hajer et al. (2020), Hanachi et al. (2012) and Sonnenberg and Vom Brocke (2014)

Table 3
Main focus of process mining perspectives in the reviewed articles.

Perspective	Articles
Control-flow	Augusto et al. (2016), Bemthuis et al. (2019, 2020), Cabac et al. (2006), Ferreira et al. (2013), Ito et al. (2018), Larsen et al. (2019), Nesterov et al. (2022), Ou-Yang and Winarjo (2011), Polyvyanyy et al. (2020), Rozinat et al. (2009), Sohail et al. (2021), Šperka et al. (2013) and Szimanski et al. (2013)
Organizational	Cabac et al. (2006), Ferreira et al. (2013), Hanachi et al. (2012), Ito et al. (2018) and Larsen et al. (2019)
Time	Bemthuis et al. (2019, 2020), Ferreira et al. (2013), Ito et al. (2018), Rozinat et al. (2009) and Sohail et al. (2021)
Case	Rozinat et al. (2009)

model of agent groups and individuals, depicting causal dependencies between activities, process flow, and activity change frequencies. Ou-Yang and Winarjo (2011) use event logs for each agent and convert them into Petri-net models, aiming to identify connections among agents by analyzing activity sequence in a MAS. Hanachi et al. (2012) mine organizational structures that describe interactions between process performers. Ferreira et al. (2013) employ a heuristics miner to analyze data showing frequencies and use a social network miner. Šperka et al. (2013) extract sequences of actions performed by agents. Szimanski et al. (2013) use metrics to analyze process models expressed as hierarchical Markov models, focusing on structure and complexity measured in density, control-flow, size, and modularity. Metrics are calculated separately for macro-model and each micro-model (Szimanski et al., 2013). Augusto et al. (2016) construct causal net models representing direct causal relations between events, using smaller models to communicate with practitioners and larger models for simulation. Ito et al. (2018) use events logs from a MAS to discover a process model, including frequencies, and analyze relationships among agents. Larsen et al. (2019) generate graphs depicting how organizational structures handle events and similar-task graph showing which units work on the same task. They also create a role-specific process model. Bemthuis et al. (2019) use an inductive miner to obtain a process model showing frequencies and average activity durations. Bemthuis et al. (2020) investigate the order and mean duration of activities for products moved by autonomous vehicles, focusing on specific scenarios and product types. Polyvyanyy et al. (2020) apply a process discovery technique to construct a model from traces, focusing mainly on control-flow. Sohail et al. (2021) generate a process model as a directly-follows graph, visualizing frequencies and duration of events. A dotted chart shows the duration of event traces. Nesterov et al. (2022) use the discovered order of agent-executed activities, linking causalities to interface patterns.

4.2.3. Conformance checking techniques

Rozinat et al. (2009) compare agents' real-world behavior with that described in a rule book. They provide examples of how observed rules coincide with normative rules. Bemthuis et al. (2019) use three process mining discovery algorithms to determine the fitness, precision, and generalization of the obtained process models for a total of 27 scenarios. The approach presented by Mecheraoui et al. (2020) obtains conformance diagnostics between projected nested Petri-nets and MAS-generated event logs. They check the fitness of a nested Petri-net to the event logs. Polyvyanyy et al. (2020) check fragments of an agent's trace for conformance with a retained model. Conformance diagnostics infer insights into the agent's goals. Nesterov et al. (2022) measure the complexity of agent interactions by assessing the number of neighboring transitions corresponding to behaviors of different agents. They estimate precision and simplicity of a reference process model, which is discovered directly and decompositionally, concerning artificial event logs from the reference model.

4.2.4. Event logs

Hanachi et al. (2012) enhance event logs using a performance-based agent communication language to capture conversations among workflow participants. Sonnenberg and Vom Brocke (2014) link economic events, activities, and resource availability changes to entities in event records. Their data structure allows for process-oriented accounting and account-oriented process management. Fauzan et al. (2019) propose an approach for generating potential future traces and event logs. Hajer et al. (2020) outline steps for preprocessing data to transform unstructured log files into structured logs suitable for process mining.

4.3. Application domains

Table 4 summarizes the diverse application domains in which the integration of ABMS with process mining has been explored. Our review includes both broad investigations and domain-specific case studies. Several studies focus on healthcare, logistics, purchasing, finance, robotics, and privacy. Additionally, Polyvyanyy et al. (2020) evaluate their approach using three real-world event logs, namely those documenting activities of daily living, building permit applications, and environmental permit applications.

In healthcare, integrating process mining with ABMS offers concrete benefits for optimizing clinical pathways and resource allocation. For example, process mining techniques extract detailed causal nets from hospital databases, which are then converted into state charts for simulation purposes (Augusto et al., 2016). This method enables granular

Table 4
Application domains and the corresponding reviewed articles.

Domain	Articles
Healthcare	Augusto et al. (2016), Larsen et al. (2019) and Sohail et al. (2021)
Logistics	Bemthuis et al. (2019, 2020) and Fauzan et al. (2019)
Purchasing	Ferreira et al. (2013), Šperka et al. (2013) and Szimanski et al. (2013)
Finance	Ito et al. (2018) and Sonnenberg and Vom Brocke (2014)
Robotics	Ou-Yang and Winarjo (2011) and Rozinat et al. (2009)
Privacy	Sohail et al. (2021)
Other	Polyvyanyy et al. (2020)

analyses of patient flows and treatment decisions. It also allows the simulation of various what-if scenarios to inform clinical decision-making. Furthermore, validating simulation outputs against real-world event logs, such as those from emergency room settings (Larsen et al., 2019), contributes to that agent behaviors and interactions reflect the complexities of clinical processes. This synergy enhances the reliability of simulation models and supports data-driven improvements in patient care, while addressing challenges related to data quality and process variability (Sohail et al., 2021).

In logistics and purchasing domains, similar advantages are evident. Agent-based simulations model complex interactions in supply chains and trading environments, where individual agent decisions directly affect overall system performance (Bemthuis et al., 2019, 2020; Fauzan et al., 2019). Process mining extracts hidden patterns from low-level event logs, thereby refining agent decision-rules and enabling continuous validation of simulation models. Studies in purchasing have demonstrated that hierarchical Markov models can bridge the gap between high-level process definitions and nuanced agent behaviors during trading operations (Ferreira et al., 2013; Šperka et al., 2013; Szimanski et al., 2013).

In finance, process mining has been applied to assess process conformance and to support the modeling of financial transactions. For example, studies have employed process mining techniques to analyze the alignment between recorded financial data and pre-defined process models, thereby providing insights into model accuracy and operational efficiency (Ito et al., 2018; Sonnenberg & Vom Brocke, 2014).

In robotics, process mining further enhances ABMS by detecting emergent behaviors and identifying bottlenecks, which are critical for optimizing multi-agent coordination and system responsiveness (Ou-Yang & Winarjo, 2011; Rozinat et al., 2009). Additionally, goal recognition techniques that leverage process mining outputs provide novel capabilities to predict agent intentions in real-world settings (Polyvyanyy et al., 2020). This body of work underscores the potential of integrating these methodologies across various application domains.

4.4. Outlook

Recent developments have introduced noteworthy new scientific articles published after the cutoff date of our systematic literature review, covering both theoretical advances and real-world applications in the overlap between process mining and ABMS. Below, we incorporate these recent studies, highlighting their core content and relevance.

Duranti, Giorgini, Mazzullo, Robol, and Roveri (2024) propose a pipeline that integrates large language models (LLMs) with formal verification modules. Their method transforms natural-language instructions into temporal logic constraints, letting high-level user prompts be converted into precise process specifications. Related work explores conversational systems for BPM. For instance, Casciani, Bernardi, Cimitile, and Marrella (2024) show how LLM-powered dialogues can bridge technical process tasks and human stakeholders, while Fontenla-Seco et al. (2023) describe a “C-4PM” framework that uses LLMs to interpret user queries and then applies declarative engines for constraint checking and conformance analysis.

Agent intelligence and autonomous decision-making represent another focal point of these recent contributions. Su, Polyvyanyy, Lipovetzky, Sardiña, and van Beest (2023) introduce fast and accurate goal recognition using skill models derived from event logs, which is especially useful in contexts where formal domain theories remain incomplete. They later expands this concept to dynamic environments by outlining adaptive retraining techniques that address shifting processes or behaviors (Su, Polyvyanyy, Lipovetzky, Sardiña, & van Beest, 2024). Process simulation also receives attention through Sulis (2022), who employ agent-based modeling to optimize healthcare logistics, comparing hospital-centric and home-based care and revealing potential ecological benefits. Bemthuis, Govers, and Lazarova-Molnar (2023) and Bemthuis and Lazarova-Molnar (2023) highlight how outlier detection in event logs can reinforce face validity in agent-based simulations. Their work demonstrates how targeted process mining can isolate improbable agent behaviors that might skew key performance indicators or emergent dynamics.

In the area of resource-focused modeling, Kirchdorfer, Blümel, Kampik, Van der Aa, and Stuckenschmidt (2024) present AgentSimulator, a system that infers multi-agent behaviors and resource utilization from historical data. This approach is relevant to processes without a central orchestrator. Similarly, Bemthuis and Lazarova-Molnar (2022) examine how to discover agent decision rules directly from event logs, using the Schelling segregation model as an illustrative example. Both studies aim to reduce the burden on developers by minimizing manual rule specification, thus supporting more faithful modeling of real-world behaviors.

Some works address process improvement and anomaly detection through reinforcement learning. Elaziz, Fathalla, and Shaheen (2023) integrate a deep reinforcement learning agent into a system that learns from a small set of labeled anomalies, using variational autoencoders and LSTM-based exploration to detect novel anomaly classes with high accuracy. Furthermore, Soliman, Mostafa, and Younis (2024) encode business processes as state–action pairs, letting an reinforcement learning agent avoid bottlenecks and select high-impact actions. Finally, Shen, Polyvyanyy, Lipovetzky, and Kampik (2024) propose Agent System Event Data (ASED), a data model that captures multi-agent interactions and extends beyond standard case-based logs in both scale and granularity.

Taken together, these recent findings highlight emerging directions that bring together process mining, ABMS, and advanced AI methods—particularly LLMs and reinforcement learning algorithms. Their shared focus on adaptive, interpretable, and automated solutions underlines the value of integrated approaches for data-driven process management.

5. Open challenges and future outlook

The integration of process mining with ABMS presents new opportunities for a broader range of approaches. This synergy can deepen our understanding of complex systems, such as socio-technical systems, and spur innovations in agent-based and process mining techniques. In this section, we discuss open challenges, emerging opportunities, and future research directions.

To provide a comprehensive overview, we have included additional articles beyond those obtained through our systematic review. This approach broadens our perspective, offers further insights, and helps identify research challenges and directions not covered in the initial pool. Incorporating these supplementary articles enhances the accuracy and robustness of our representation of the available evidence.

The following part discusses open challenges and future outlooks related to several topics: data requirements and semantics (Section 5.1), event log formatting and object-centric process mining (Section 5.2), agent intelligence (Section 5.3), verification and validation of agent-based systems through process mining (Section 5.4), methods for interaction between agents and process mining (Section 5.5), process mining to steer simulation optimization methods (Section 5.6), tool support and lack of guidelines (Section 5.7), and lastly some miscellaneous topics (Section 5.8).

5.1. Data requirements and semantics

While data produced by agent-based systems and process mining is abundant, extracting this data poses challenges for both fields (Halaška & Šperka, 2018). The value of process mining techniques depends heavily on data quality. Without proper attention, poor data quality and quantity can exacerbate issues in subsequent analysis. Our systematic review revealed that none of the articles explicitly addressed the impact of data quality issues, such as incomplete or uncertain data. There is a need to develop robust techniques to handle these challenges and evaluate the accuracy of data sources.

Enhancing objects — represented by agents and event logs — with more context-aware and fine-grained data-gathering capabilities can increase the sophistication and complexity of data and process models. However, factors that enrich event logs, such as social, environmental, economic, and political conditions, receive limited attention. Most studies address relatively simple data structures, despite the well-known heterogeneity of agents, their numerous interactions, and complex topologies. For example, Mecheraoui et al. (2020) distinguish between three types of steps within a MAS: element-autonomous steps (the execution of an activity a_1 by an agent r_1), system-autonomous steps (the execution of an activity a by the system SN, involving n agents), and synchronization steps (the simultaneous execution of activity a by SN and activities $a_1, \ldots, a_n$ by agents $r_1, \ldots, r_n$).

Another promising direction involves the use of agent ontologies. Several papers (e.g., Ito et al., 2018; Sohail et al., 2021; Sonnenberg & Vom Brocke, 2014) focus on the REA ontology, which defines how agents manage economic resources and transfer or receive control from other agents. Such ontologies provide a shared semantic representation within a specific domain. They can simplify complexity, organize data into actionable information and knowledge, promote the reuse of domain knowledge, and make domain assumptions explicit.

As data granularity increases, extracted process models can quickly become complex and convoluted, resulting in so-called “Spaghetti” or “Lasagna” models (van der Aalst, 2016). This growing complexity presents challenges for both ABMS and process mining. It is essential to define coherent data structures, integration architectures, and metadata standards that enable the coupling of process and agent model extraction and analysis techniques. This approach has already yielded valuable insights in domains such as finance (Sonnenberg & Vom Brocke, 2014), logistics (Piest, Cutinha, Bemthuis, & Bukhsh, 2021), and manufacturing (Friederich, Lugaresi, Lazarova-Molnar, & Matta, 2022).

Investigating the coherence of agents’ state changes with constructs like ordered sequences or time is also important. Future research should focus on implementing semantic features that can improve results and represent real-world data more accurately, while processing data in diverse forms—continuous, ad hoc, time-based, or state-change-based. Machine learning techniques and domain ontologies could be promising avenues. Using domain ontologies and specifications may help adapt quickly to data changes and lower the entry barrier for data interaction. The use of standards such as the Overview, Design Concepts, and Details (ODD) protocol developed by Grimm et al. (2020) is recommended for describing agent-based models. Further exploration of event data models, such as the Agent System Event Data (ASED) model proposed by Shen et al. (2024), could enhance the analysis of agent interactions and the dimensional representation of event data in integrated ABMS and process mining frameworks.

Finally, prioritizing data-centric research over purely model- or process-centric approaches is key. Researchers often focus on designing the “right” process or agent models (“How can we change the model to improve performance?”), while systematically improving data quality to enhance model accuracy is frequently overlooked (“How can we improve the accuracy of the model by enhancing data quality?”). Generative models like conditional generative adversarial networks (GANs) are emerging as promising tools in this context, enabling the creation of synthetic event data that can rigorously evaluate and refine mining techniques. Moreover, a common assumption in process mining is that the process remains unchanged during the recorded period (Bose, van der Aalst, Žliobaitė, & Pechenizkiy, 2011). This assumption often proves incorrect due to concept drift, where processes evolve during case handling. Rather than analyzing large datasets with noisy deviations, it may be more beneficial to examine smaller, interpretable datasets that effectively train algorithms (Sorscher, Geirhos, Shekhar, Ganguli, & Morcos, 2022). These datasets should encapsulate meaningful contributions, and substantial design efforts may be required. Agents that automate tasks and collaborate closely with humans could play a pivotal role. Exploring streaming data — where knowledge evolves during analysis — also presents an intriguing avenue. Adopting a data-centric mindset could drive significant innovation in the future.

5.2. Event log formatting and object-centric process mining

Although using event logs extracted from agent-based systems for process mining has been demonstrated, many studies pay little attention to the expressive power of event records. Some studies have used additional attributes of event logs. For example, Ito et al. (2018) include data beyond timestamps and event performers, such as requested quantity and quoted price per unit. Enriching event logs could help identify new organizational and informational models (Hanachi et al., 2012). In addition, Kirchdorfer et al. (2024) underscore the importance of logging resource-centric data in multi-agent environments, while Fontenla-Seco et al. (2023) demonstrate that advanced log architectures can be employed in declarative contexts to enable enriched analysis. In ABMS, where multiple agents have different views of the same process, it is easy to lose track of the overall process. Additionally, an event may relate to various cases (convergence), or a series of activities may exist within a single case (divergence) (van der Aalst, 2019). Traditional process mining techniques fail to address these concerns, whereas recent developments in object-centric process mining offer a promising solution. In object-centric process mining, events can relate to objects of different types (van der Aalst, 2019).

To our knowledge, combining ABMS with object-centric process mining has not been investigated. Applying these novel techniques to ABMS has great potential, as agents inherently interact with other agents related to the same or different processes. MASs usually incorporate multiple objects and types of agents, each addressing distinct concerns (Garcia, Silva, Chavez, & Lucena, 2002). Agents are natural candidates for representing object-oriented models and systems. Since agents typically do not operate in isolation and interactions occur through bridging events where agents exchange data within a larger system, examining different logging formats and attributes could help investigate hierarchical relationships and interrelationships of agent processes more comprehensively.

5.3. Agent intelligence

While basic capabilities of agents acting intelligently have been demonstrated using process mining techniques, much remains to be explored to tap into the full potential of the ABMS paradigm. Autonomous agents can acquire data from their environment and decide how to relate environmental stimuli to their behaviors to attain certain goals. Some agents may follow predefined behavioral patterns, while others acquire dynamic behaviors based on learning and adaptation mechanisms. To advance ABMS development, incorporating artificial intelligence (AI) techniques is suggested. For instance, Bemthuis et al. (2020) describe an approach where agents adapt their decisions based on analyzing emergent behaviors using process mining. Implementing local intelligence for each agent — such as having agents decide their actions based on their goals or forming coalitions to make negotiations more advantageous — is intriguing (Ito et al., 2018). Agents can adjust their behaviors based on extracted knowledge from event logs (Bemthuis et al., 2019). However, many studies are limited to extracting event logs and discovering a process model from an existing MAS, without leveraging these insights to steer agent decision-making or enhance problem-solving abilities in complex environments. It is crucial to explore how process insights and AI can further empower agents and enhance their intelligence. For example, recent progress explores data-driven agent intelligence for on-the-fly adaptation (Su et al., 2023, 2024), while reinforcement learning approaches (e.g., Elaziz et al., 2023; Soliman et al., 2024) demonstrate how agents can optimize process steps autonomously.

Future research should consider distributed and decentralized forms of agent intelligence. Agents may be responsible for individual learning patterns — such as in multi-agent reinforcement learning — while interacting and communicating with other agents using knowledge graphs obtained through process mining techniques. Leveraging AI techniques can better equip agents to function autonomously, adapt to dynamic environments, and improve the efficacy of ABMS. A key aspect is the trade-off between exploration and exploitation in agent learning. Future studies could investigate how agents balance the need to explore new strategies with exploiting known successful behaviors, especially when informed by insights derived from process mining. Incorporating adaptive mechanisms that adjust this balance based on real-time process data may enhance agents' ability to learn optimally in complex environments.

Furthermore, most research focuses on reactive use of event logs and process mining techniques. Patterns like violations or delays are identified and addressed only after they occur. Predictive process monitoring, which attempts to predict future states of ongoing, incomplete process executions (Ly, Maggi, Montali, Rinderle-Ma, & van der Aalst, 2015), warrants more attention. The approach by Fauzan et al. (2019) generates potential future traces of event logs from a MAS, primarily using random distribution functions. However, this method does not explore advanced prediction techniques or subsequent steps for prescriptive purposes. The interplay between agent technologies and predictive process monitoring holds promise for advancing the field. For example, agents can contribute to both the training phase (learning from historical traces) and the prediction phase (supporting predictions of potential execution outcomes). Another approach involves generating an agent-based prediction model from data, utilizing agent organization frameworks as suggested by Larsen et al. (2019).

Process mining can also augment research on various transitions identified in agent-based systems, such as relationships among activities, communication patterns, and state changes. The field is progressively conceptualizing observable agent behaviors revealed and shaped by process mining methods. However, promising areas remain unexplored. For example, examining how individuals and groups adapt their work towards goals from various macro-level and micro-level perspectives could be intriguing (e.g., Ghasemi & Amyot, 2020; Yan, Hu, Liao, & Wang, 2014). Further research is required to handle advanced agent communication protocols (Cabac et al., 2006) and study agent group dynamics (Rozinat et al., 2009). Process mining has the potential to offer real-time feedback to agents that can reflect their processes, representing a promising area of research. Investigating non-stationary environments — where environments continuously change — also presents an interesting direction (Polyvyanyy et al., 2020). In this context, the concept of 'forgetting' data records used to construct models could be useful for generating robust models. There is ample opportunity to achieve closer integration of process mining and the intelligence manifested by agents, which needs to be explored in future research.

5.4. Verification and validation of agent-based systems and models by means of process mining

Beyond analyzing the performance of a MAS, process mining has been applied as a tool for verifying ("building the model right") and validating ("building the right model") agent-based models. The capability of process mining to verify properties of agent-based systems has been demonstrated in various applications. For instance, research has addressed the verification of behavioral properties of agents (Halaška & Šperka, 2018; Tour et al., 2021), monitoring and debugging of MAS (Cabac et al., 2006), and correctness checking using social network analysis (Ito et al., 2018). In the validation phase, process mining can aggregate trace data observed from the running system and visualize, formally analyze, or compare design models with models representing reality to validate the behavior of the agent-based system (Bemthuis et al., 2023; Bemthuis & Lazarova-Molnar, 2023; Cabac et al., 2006).

Although applications of process mining for verification and validation in ABMS exist, there appears to be no consensus on the appropriate process mining-based techniques for these purposes. Such methods mainly revolve around specific case studies within particular domains (e.g., Bemthuis et al., 2023). One key challenge is the inherent complexity typically represented in agent-based systems (Baqueiro et al., 2009). Real-world processes are often more complex than those captured by process mining (Tour et al., 2021) and ABMS assumptions. Improving the intended outcome and correctness of an agent-based system through process mining, as well as enhancing verification and validation through process mining techniques, is an ongoing research direction. Process mining can be a key ingredient in designing new methods for verifying and validating ABMS efforts.

Process mining has the potential to be employed in more phases of designing, modeling, and analyzing ABMS processes. While there have been developments toward a more integrated framework for simulation supported by process mining, the development of a unified methodology remains an open issue (Bemthuis, Govers, & Asadi, 2024; Keith Norambuena, 2018). There is significant potential for further advancements in specifying how well-known concepts of verification and validation in (agent-based) modeling and simulation processes relate to process mining. Therefore, it is worthwhile to develop standard verification and validation methodologies for ABMS based on process mining techniques. These can serve as suitable platforms for investigating ABMS processes more comprehensively.

5.5. Methods for agent and process mining interactions

While existing studies provide useful ideas and methods mainly focused on ABMS techniques followed by process mining techniques (see Table 1), there is limited evidence on the implementation of other types of interactions between process mining and ABMS, as described in Section 4. One reason could be that process mining, being a relatively young field, is still exploring synergetic effects with ABMS. For example, ABMS is expected to improve the quality and impact of constructed process models (Bemthuis et al., 2019). To enable synergetic effects, the categorization discussed in Section 4 may serve as a guiding framework for emerging research on analyzing complex systems through process mining and ABMS. An agent may observe environmental behavior not identified by constrained process mining techniques, and this information could enhance process mining techniques.

There is also scope for improvement in research related to ABMS methods directly followed by process mining techniques, as supported by calls for research on translating process mining output to agent properties, such as organization constraints (Larsen et al., 2019). Furthermore, research on algorithms for process mining conformance and enhancement techniques combined with ABMS is underrepresented (see Table 2). One direction to explore is applying conformance checking on MAS models in a "nets-within-nets" manner (Carrasquel, Lomazova, & Itkin, 2019). Recent advancements in agent-based process mining, such as the algorithm proposed by Tour, Polyvyanyy, Kalenkova, and Senderovich (2023), emphasize the benefits of modular discovery of agents and their interactions from event data, providing an alternative to conventional process discovery approaches. Designs for interactions between process mining and ABMS methods are still in early stages, and further research could broaden their utilization.

Many researchers have reported challenges in discovering and inferring agent models from data using process mining methods. The inherent complexity of agent models is not yet fully understood and warrants further study through process mining (Bemthuis & Lazarova-Molnar, 2022). Direct discovery from an event log of a MAS may result in unclear model structures and overgeneralization of individual agent behaviors (Nesterov et al., 2022). Similarly, the inability to group agents based on their type can lead to complex and overfitted agent models (Tour et al., 2021). One potential solution could be defining a similarity measure between agents. Studying the discovered relationship between events at different levels of granularity (e.g., macro and micro) can help better understand how agents perform activities at runtime (Ferreira, Szimanski, & Ralha, 2012). Research on analyzing log data to obtain an overall picture, as well as behavioral sub-models of classes of agents, is promising (Rozinat et al., 2009). New algorithms should be developed to handle situations where one data record from the log file is relevant to multiple agents, the environment, a single agent, or not related to any agent (Tour et al., 2021). Presently, there are limited signs of agent model discovery beyond direct discovery based on agent log files.

Designing efficient algorithms that consider algorithmic runtime is necessary, as handling large-scale data within time constraints can be challenging. Pruning strategies and high-utility process mining techniques can extract relevant knowledge (Belhadi, Djenouri, Diaz, Houssein, & Lin, 2021). However, it is important to focus on achieving appropriate interpretations of dense and large mined process models, such as Spaghetti or Lasagna models. For example, identifying components that represent behavioral patterns of selected agents (Šperka et al., 2013). There is no consensus on which parameters of ABMS or process mining, or their combination, yield the best performance. This can be useful when dealing with large-scale applications with a training phase for algorithms that have an optimal time span for collecting these parameters. Exploring the tuning of a particular process discovery algorithm with respect to perturbations in the representation bias could also be valuable (Bemthuis et al., 2019). Investigating statistical comparisons of deviating parameters or relaxing assumptions, especially when only a subset of the dataset is utilized, could be another direction.

5.6. Process mining to guide (agent-based) simulation optimization methods

Although not restricted to the ABMS paradigm, it is worth mentioning that process mining may also be applicable in simulation optimization methods. Simulation optimization can be defined as finding the best input variable values from among all possibilities without the need for explicitly evaluating each possibility (Carson & Maria, 1997). It is important to understand that the evaluation is performed via simulation, and the output generated is inherently stochastic, thus not fully revealing the value of the input parameters under consideration. The objective is to minimize the resources spent while maximizing the information obtained from a simulation run, replication, or experiment.

Simulation optimization can be particularly useful in simulating MASs, given that these systems typically possess a multitude of potential input factors, exhibit stochastic behavior, and produce relatively noisy output. Process mining can support the selection process for identifying promising candidate input factors (potentially subject to constraints) for simulation. For example, methods based on process mining, which utilize knowledge of the macro-model, can aid in identifying the most suitable solution in fewer runs (Ferreira et al., 2013).

Process mining could open new avenues for optimizing agent-based simulations through simulation optimization. For instance, process mining techniques can function as a meta-modeling heuristic (Greasley & Edwards, 2021) by incorporating these techniques into a higher-level procedure that uses characteristics of the simulation process (e.g., observed parameters and runtime) as input for an event log. This event log can then be analyzed and enriched using process mining techniques to determine the next set of promising input variable values for evaluation via simulation.

Another example involves using observed discrepancies between real-life event logs and other system logs produced by a simulation model to elucidate agent-based model simplifications and assumptions. Optimization can be used to tune the model to coincide with reality. Data-driven insights into such deviations could help determine the quality of parametric input, even in the presence of output noise. However, careful consideration must be given to how process mining fits within simulation optimization, especially since traditional methods assume that simulation models are black-box models.

A third example concerns the potential for process mining to act as a differentiation technique in estimating simulation derivatives. The quality of mined process models (expressed through measures like recall and precision), along with other quality indicators obtained when analyzing various process flows in more detail (such as exceptional behavior and bottlenecks), could advance the search for input parameters for a simulation. In particular, process mining might support the detection of unforeseen implicit interaction patterns that emerge at runtime (Cabac et al., 2006). Further development of the possible connections and interplay between process mining and agent-based simulation (Ferreira et al., 2013; Ito et al., 2018), as well as efforts in simulation optimization, is both desirable and worth investigation.

For more inspiration and discussion on simulation optimization methods, interested readers are referred to the works of Amaran, Sahinidis, Sharda, and Bury (2016), Figueira and Almada-Lobo (2014) and Fu, Fu, and Michael (2015). For a review of enhancing simulation with big data analytics, which also addresses process mining, see Greasley and Edwards (2021).

5.7. Tool support and lack of guidelines

One challenge that needs to be addressed is the limited availability, customization, and development of tool support (Augusto et al., 2016; Cabac et al., 2006; Rozinat et al., 2009), which can lead to issues related to utility, usability, and scalability. This limitation could indicate that the field is still in its early stages and that validation or adoption needs refinement. Another issue is the lack of compatibility between process mining and ABMS tools. To promote practical adoption, it is key to have suitable tools flexible enough to be tailored to specific domains. A solution would be simulation frameworks and tools that can automatically generate event and agent log files.

Automating data processing pipelines is essential, as many studies still rely on manual steps to achieve meaningful outcomes. For example, Larsen et al. (2019) propose a nine-step pipeline involving event logs, BPMN models, and agent-based systems. Activities are typically associated with different tools and external sources to achieve analysis over multiple execution steps, which may hamper reproducibility and convenience. An automated pipeline would streamline data extraction, transformation, and integration, while enhancing compliance efforts—

an area that remains underexplored (Castellanos Ardila, Gallina, & Ul Muram, 2022). Future advancements will likely depend on developing integrated approaches that seamlessly automate ABMS and process mining workflows.

Furthermore, a major limitation in current studies is the lack of sufficient guidelines for adopting proposed methods. Some recent conversational frameworks (e.g., Casciani et al., 2024; Fontenla-Seco et al., 2023) show promise in bridging technical complexities and broader stakeholder needs, but more systematic guidelines remain necessary (Szimanski et al., 2013). The absence of guidelines may hinder individuals with little or no prior knowledge in the process mining or ABMS field from using the proposed methods. In complex application areas frequently considered by ABMS, users must be confident that a proposed method will function as intended.

Finally, despite many studies demonstrating the applicability of open-source tools, source codes, and datasets, the transparency and accessibility of the investigated research practices are not always optimal and warrant greater attention. This lack of transparency can impede usability and raise concerns about reproducibility. Introducing commonly used datasets could promote reproducibility and comparison among different ABMS models. Therefore, developing tool support and guidelines that are more user-friendly and comprehensible is necessary. Disseminating best practices and recommendations could enhance future research efforts.

5.8. Miscellaneous topics

Several additional challenges extend beyond the immediate scope of this literature review. A significant challenge is to investigate how the evolution of agent technologies, including advanced exchanges among agents about planning, coordinating, monitoring, and evaluation, influences the collective trajectory. This can be done by analyzing scenarios and applications using process mining techniques. Fusing elements of the process mining discipline with the ABMS paradigm is promising, as it regards both the behaviors an individual agent undertakes and the collective, and encompasses a wide range of techniques originating from process mining (Bemthuis et al., 2019; Ferreira et al., 2013; Ito et al., 2018). Another significant challenge is exploring the relationship between the (uncompromising) precision of algebraic process mining techniques, the capability to detect uncommon process variants, and the quality of available log data (Flick, Cabac, Denz, & Moldt, 2010). Another open issue is the investigation of innovative methods and algorithmic approaches to examine how a sequence of underlying and potentially (partially) unobservable events evolves. This concept is primarily in its early stages, offering ample opportunities for further advancements.

Recent methodological developments support these directions. Novel data models, such as ASED (Shen et al., 2024), or transformations from LLM-based queries into formal logic (Duranti et al., 2024), hint at future cross-disciplinary methods, bridging advanced AI and process modeling. Such methods could promote further integration between sophisticated AI approaches and detailed process specifications.

Furthermore, integrating process mining with ABMS could establish a more robust, data-driven framework (see Section 5.1). By automating repetitive or error-prone data operations, agents enable humans to concentrate on creative or domain-focused objectives. For example, agents can collect and refine data or adjust discovery algorithm parameters, while experts scrutinize anomalies and address data gaps. Although studies of collaborative human-agent paradigms are still emerging, the adoption of digital twin and metaverse technologies may offer more responsive approaches to runtime interventions in complex systems.

Recent advances in large-scale multi-agent simulations, such as Project SID (AL et al., 2024) and AgentVerse (Chen et al., 2023), demonstrate the potential for emergent dynamics and improved human-agent collaboration. Integrating such simulations with process mining offers fresh insights into agent societies, aligning with process science principles that focus on socio-technical change (vom Brocke et al., 2024). Furthermore, combining LLMs (Casciani et al., 2024; Duranti et al., 2024; Fontenla-Seco et al., 2023; Guo et al., 2024) and agentic AI (Acharya, Kuppan, & Divya, 2025; Russell & Norvig, 2021; Wooldridge, 2009) can enhance both autonomy and data interpretation, enabling proactive anomaly detection, context-aware interventions, and more intuitive human-agent interactions. These models can also advance process mining by supporting semantics-aware tasks and improved benchmarks (Berti, Kourani and van der Aalst, 2024; Berti, Kourani, Hafke, Li and Schuster, 2024; Rebmann, Schmidt, Glavaš, & van Der Aa, 2024), ultimately contributing to adaptive and resilient systems that draw on the complementary strengths of humans and agents.

For future research, the initial classification depicted in Fig. 4 could aid in developing new metamodels and formalisms that are suitable for representing agent-based models and systems as well as process mining techniques. A key challenge in achieving this is to clarify connections between agents, process mining, and underlying constructs. Additionally, none of the reviewed papers reported a comprehensive comparative study of approaches using ABMS and process mining, while this is key for (1) informing users interested in adopting a new method, (2) helping identify similar situations where a method can be applied, and (3) facilitating the selection of an appropriate method for a particular situation. However, there have been some initial efforts reported on comparing the performance of various agent-process mining configurations, such as using multiple process mining discovery algorithms (Bemthuis et al., 2019), agent rule settings (Bemthuis et al., 2019, 2020), or varying the number of events (Belhadi et al., 2021). Nonetheless, the level of investigation is still preliminary and limited to a small set of variations. Tour et al. (2021) also call for measures and methods to compare MAS model logs and real-world process logs. Moreover, there is still a significantly higher focus on the individual fields of process mining or ABMS, rather than on the combination of ABMS and process mining. However, cross-fertilization may have greater potential for practical adoption. Finally, further exploration across various application domains and industry sectors will steer additional research directions.

6. Conclusion and discussion

This paper presented a systematic literature review on the integration of process mining and ABMS, identifying key challenges and future research directions. From an initial pool of 189 studies, a final set of 20 was analyzed in detail, uncovering research gaps and outlining opportunities for further exploration. While existing work demonstrates the potential of integrating ABMS and process mining, significant challenges remain.

Among the identified interaction types, ABMS followed by process mining (Type V) is the most prevalent, whereas alternating interactions (Type III) and nested iterations (Types I and II) remain mostly underexplored and require empirical validation. Current research predominantly focuses on process discovery, with conformance checking and enhancement methods receiving limited attention. Similarly, the control-flow perspective dominates process mining applications in ABMS, while organizational, time, and case perspectives are underrepresented. Despite multiple integration approaches, the practical benefits and comparative advantages of different methods remain poorly understood.

Key challenges and research directions include data requirements and semantics, event log formatting, object-centric process mining, agent intelligence, verification and validation, and simulation optimization. While process mining has proven effective for analyzing emergent agent behaviors and verifying ABMS outcomes, its potential for decision support and real-time agent adaptation remains largely unexplored. Future work should formalize methodological frameworks, provide standardized evaluation metrics, and establish best practices for data collection and tool integration, ensuring greater applicability and alignment with open science principles. In this regard, we hypothesize that integrating process mining with agent-based process discovery frameworks can reduce model complexity and enhance predictive accuracy, as demonstrated in patient flow simulations. Furthermore, standardized evaluation metrics for agent-based models may facilitate robust comparisons with traditional simulation approaches, thereby strengthening decision support. Finally, developing a comprehensive framework for real-time agent adaptation — achieved through continuous process monitoring and predictive process mining — could markedly improve system responsiveness in dynamic environments.

Although this review is not exhaustive, the insights presented provide a foundation for advancing process mining–ABMS integration. Future research could refine this work by developing classification schemes or maturity models to enhance the understanding of ABMS and process mining synergies. Comparative studies with alternative modeling paradigms (e.g., discrete-event simulation, system dynamics) are key to delineate the unique advantages of process mining–ABMS integration. Strengthening the interplay between these fields has the potential to cross-pollinate innovations and drive methodological advancements. This work aims to stimulate further exploration and innovation in this evolving research domain.

CRediT authorship contribution statement

Rob H. Bemthuis: Conceptualization, Methodology, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Sanja Lazarova-Molnar:** Conceptualization, Supervision, Writing - review & editing.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to receive suggestions for improving readability and writing style. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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