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TECHNICAL CONTRIBUTION

Business Process Management and Artificial Intelligence

Literature Survey and Future Research

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Abstract
The field of Business Process Management (BPM) has several academic roots, in particular management science and informatics. In particular at the intersection of BPM and Artificial Intelligence (AI), a vibrant interdisciplinary field of research evolved. In this survey, we review prior work from three perspectives, namely, (a) from the perspective of BPM we focus on modeling, analysis, redesign, implementation, and monitoring of processes; (b) from the perspective of AI we focus on natural language processing, knowledge representation, automated reasoning, machine learning, computer vision, and robotics; (c) from the perspective of application domains we focus on domains such as process-aware information systems, manufacturing, and healthcare. Additionally, we discuss future research challenges and opportunities.

Keywords Business process · Machine learning · Robotic process automation

1 Motivation

As many terms in the engineering field, the term "Business Process Management" (BPM) denotes a problem, a solution, and the field studying these problems and solutions [26].

- *Problem:* How to manage processes from an economic point of view? Such a problem typically includes subproblems as designing a business strategy, understanding and modeling processes, automating, monitoring and improving processes. Additionally, BPM does not only ask for the management of one process, but several processes, which are typically entangled, e.g., sourcing is entangled with production, production is entangled with selling, all processes are entangled with human resource management, finance, organization, general management, and many more.
- *Solution:* The mentioned problem often has a specific solution. However, many of the options available in the software market do not focus on a custom or individual software solution, but rather on standard software used for more general purposes. For instance, there exist standard tools for modeling, e.g., SAP Signavio, BPM-Camunda modeler, ARIS modeling framework, or ADONIS; ERP systems for process execution, e.g., SAP Hana, Salesforce, Microsoft Navision; monitoring tools, e.g., Celonis, Fluxicon, Apromore, ARIS; or model-based development tools, also known as "low-code" or "no-code development", e.g., Mentrix, depending on particular industries and sizes of enterprises.
- *Academic field of BPM:* BPM is an established field, as demonstrated by well-known monographs, e.g., Weske [77], Dumas et al. [23], and handbooks [73]; renowned journals and conferences, such as BPMJ (Business Process Management Journal), BPM (Business Process Management) conference, ICPM (International Conference on Process Mining); established teaching programs (e.g., in German-speaking countries there is an well-established teaching curriculum); particular denominations of chairs, e.g., the Process and Data Science chair at the RWTH Aachen University, the

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Besides the current hype around the idea of Artificial Intelligence (AI), research in BPM interrelates with research in the field of AI since many years. For example, the modeling of business processes can be viewed as one form of knowledge representation. This and many other interesting interrelationships are not only demonstrated by several publications in different conferences or journals, but also by a number of organizational and institutional efforts, as well as academic events explicitly trying to bring the different research streams together, as, for instance:

- 9 editions of the Artificial Intelligence for Business Process Management (AI4BPM) workshop at the BPM conference,
- 3 editions of the Natural Language Processing for Business Process Management (NLP4BPM) workshop at the (BPM) conference,
- the Artificial Intelligence and Business Process Management AAAI 2023 bridge program,
- the Process Management in the AI era at the IJCAI/ECAI (International Joint/European Conference on Artificial Intelligence) conference,
- 2 editions of the Generative AI for Process Mining (GenAI4PM) workshop at the ICPM conference, and
- the Robotic Process Automation (RPA) Forum at the BPM conference.
- Special issues such as the current one but also others, such as the Information Systems Special Issue *AI-Enhanced Business Process Management* or the Process Science collection *Artificial Intelligence and Processes*.

These developments clearly demonstrate that there is a lively and active research field at the intersection of BPM and AI.

Against that background, our objective is to survey the body of knowledge at such intersection. Our survey does not aim to provide a comprehensive overview of all works in the field. Such an ambition would lead to an effort in vain, for the following reasons:

- Currently the field does not have crisp and sharp borders. Hence, inclusion and exclusion criteria of particular works are not well decidable by objective criteria but would be subjective.
- Both fields, BPM and AI, are very heterogeneous with many different but often very specific results. Many particular results, although very interesting for specialists in that particular area, are not of so much interest for a more general audience. Hence, in our survey, we do not want to delve into the scientific details of all papers. Instead, we would like to give a broader view, a view from the lighthouse. This does not mean that it would not make sense to focus on a particular aspect, as done, for instance, by systematic literature reviews on specific aspects in the field (e.g., on anomaly detection [45, 53]). Against these examples, it is clear that one survey that addresses the broad field of AI and BPM cannot go into every detail and it is not our claim to do so.

However, our survey is not a completely subjective selection of the existing works. In fact, we reviewed all publications of the AI4BPM workshop (which published more than 50 papers between 2017 and 2024). Moreover, considering that there is much more work at this intersection, we also included more references for some specific topics to ensure that the survey is balanced and includes all major contributions.

Our survey is structured as follows: after this introduction, the following section introduces the theoretical background of the survey, namely our conceptualization of the fields of BPM and AI. Based on this background, Sect. 3, the core of the paper, reviews work in the field. Future research challenges are described in Sect. 4. The survey closes with some general remarks and conclusions.

2 Theoretical Background

2.1 Preliminary Remarks

The field of BPM, as well as the field of AI, are inherently interdisciplinary. As such, there is no single well-accepted theoretical understanding. For a deeper discussion of the different conceptualizations, definitions, understandings, and major (reference) theories, we point to the pertinent literature: for the field of BPM see e.g. Houy et al. [40] and vom Brocke et al. [72]; for the field of AI see General AI works [63] or AI applied to Human Resource Management [67].

Instead, we use here two well-known and accepted understandings of the two fields. We do not argue that our background is the only one possible or is superior to other conceptualizations of the field. We just argue that our review benefits from some structure and therefore we employ two well-known and, to a certain degree, well-accepted conceptualizations. Although these frameworks are comprehensive and selective to some extent, it is clear that some aspects are not covered. Additionally, between the different facets there are relationships so that some systematizations are not easily possible. Nevertheless, these frameworks provide us with some structure to review the intersection of both fields.

2.2 The Field of Business Process Management

Multiple definitions of business process, slightly different from one another, have been proposed. Among them, the one by Weske [77], who defines a business process as "a set of activities that are performed in coordination in an organizational and technical environment. These activities jointly realize a business goal". Similarly to the definition of business process, as mentioned in the introduction, the term BPM is used in different ways. Here, we focus on BPM as an academic field. As a point of reference to structure this field, we use the framework introduced by Dumas et al. [23] Based on this framework, we differentiate five aspects which are typically understood as different phases of a life cycle-structure of BPM [23, p. 22]:

- *Process identification and process discovery/as-is modeling:* The objective of this phase is to define the business problem and to identify processes. Typical results are an architecture of processes and the so-called *as-is process models*. During this phase, interviews and workshops are typically applied.
- *Process analysis:* The objective of this phase is to identify issues in processes that need to be addressed during some process redesign. The result of this phase consists in insights on weaknesses and their impact on the overall performance. Qualitative and quantitative analyses, as well as simulation approaches, are typical methods used in this phase.
- *Process redesign/process improvement:* The objective of this phase is to identify changes in the process for process improvement. This effort leads to the so-called *to-be process model*. For doing so very diverse methods are employed, such as workshops and creative techniques.
- *Process implementation:* New business processes need to be implemented taking into account both technological and organizational aspects. This results in process automation and executable process models and implies organizational changes. Instruments such as ERP, RPA and process automation are used in this phase.
- *Process monitoring:* After process implementation, some kind of monitoring and continuous improvement is necessary. This results in performance insights and possible aspects of process improvement. Typical methods used in this phase are dashboards, automated discovery and conformance checking.

2.3 The Field of Artificial Intelligence

Russel and Norvig [63] propose to structure the field of AI with respect to typical abilities that are necessary for a machine to act like a human [63, p. 2]:

- *Natural language processing (NLP):* An agent must be able to understand spoken and written natural language. In addition, an agent should be able to generate speech and natural text.
- *Knowledge representation:* An agent acquires and gains knowledge about its environment. This knowledge has to be represented in some more or less formal way inside the agent.
- *Automated reasoning:* Based on the knowledge of an agent, some conclusions can be drawn or decisions must be made. This ability of reasoning includes both classical logical reasoning, as well as some form of empirical or natural reasoning abilities.
- *Machine learning:* An outstanding human characteristic is the ability to learn new behavior based on prior experience on behavior, action, or some kind of problem solving. Similar to human learning, machine learning is of major importance.
- *Computer vision:* An agent has not only to understand language, but also images, videos, and other high-dimensional data from the real-world. This data has to be adequately acquired and processed to produce some kind of numerical or symbolic information that can be represented and used by the agent.
- *Robotics:* Robots have sensors. These sensors enable it to perceive its surroundings. The robot also has actuators. These actuators enable the robot to manipulate and interact with its surroundings. They also enable the robot to move around. In a more narrow sense and contrasted with a software robot, a robot is a tangible machine with a tangible user interface.

3 Overview of Some Existing Research

We overview existing research from the perspective of BPM (Sect. 3.1), the perspective of AI (Sect. 3.2), and the perspective of applications (Sect. 3.3).

3.1 The Perspective of Business Process Management

3.1.1 Process Identification and Process Discovery/As-is Modeling

Process identification, process discovery, or as-is-modeling of processes represents one of the first important steps in BPM. Several ideas emerged on how AI can be used here:

1. *AI-enhanced BPM strategies:* Since AI enables the automation, the AI capabilities of an organization are of importance and must be taken into account. Several works take this new perspective, such as, Zebec

et al. [84], looking at the AI-enabled capabilities developed by an organization with the adoption of AI, and Dumas et al. [22], focusing on the AI-enabled process management.
2. *Assistance for process modeling:* Since decades, some support for process modeling is a typical benefit of process modeling tools compared to simple drawing tools. Different ideas for assistance during process modeling emerged, such as activity recommendations in process modeling by using knowledge graphs of the domain [66], automatic matching between different modeling concepts, e.g., activities or events [65], or correctness and reachability analysis by using genetic algorithms [38].
3. *Automated discovery from different input sources:* Compared to assistance for process modeling, some approaches provide more comprehensive support. One line of research uses text documents of the domain to be modeled as an input. Based on that input, concepts and techniques from natural language processing are used to automatically discover process models. For example, Shing et al. [64], Gupta et al. [31], as well as Chambers et al. [15] discover process models from text documents. Some works specifically focus on the need of using background domain knowledge [56]. One further idea does not only focus on text as one source of input, but on video, audio or sensor data as other modalities of interacting process models with real- or imagined modeling domain. For example, Knoch et al. [44] focus on process detection in assembly workflows based on an assisted environment.
4. *Improved process modeling representation:* Many process modeling languages emerge more from practical utility and usability considerations and not from theoretical insights. Hence, many lines of research use particular theoretical ideas from the domain of knowledge representation to improve process modeling. For example, there are works leveraging description logics [12], others modeling aspects of uncertainty in conventional or declarative process modeling languages [24, 83], other ones using constraint-based modeling approaches for process composition [79], or new ideas for the so-called framing of processes based on AI-techniques [52].
5. *Implicit process representation:* One major stream of AI research avoids using symbolic approaches to knowledge representation in favour of sub-symbolic approaches. These ideas are also employed in process modelling. For instance, event log data representing executed activities, required resources and produced data is collected and used as training data for machine learning approaches. Therefore, business processes are no longer explicitly represented, but only implicitly, using foundational business process models. [4].

3.1.2 Process Analysis

Compared to other BPM phases, work using AI for process analysis is scarce. Currently, two streams are of interest:

1. *Root cause analysis:* Root cause analysis is a typical BPM approach for the identification and the analysis of root causes of faults in process executions, such as overly long throughput times, escalating costs, or unreliable quality of results. Some ideas exist to improve root cause analysis with techniques from the field of AI, such as the analysis of root causes with structural equation models [59], or leveraging feature selection from event logs [36].
2. *Simulation of business processes:* Simulation of business processes is a well-known approach in BPM for the analysis of complex and intertwined business processes. To improve simulation, agent-based approaches are currently discussed in the literature. For example [68] uses agents for process simulation in a hospital emergency department. Moreover, hybrid simulation approaches integrating classical simulation with predictions are also investigated [13, 51].

3.1.3 Process Redesign/Process Improvement

Initial work on process redesign focused on simple, rule-based insights to improve business processes. For example, clashes between paper-based and electronic process execution should be avoided. Other redesign patterns include empowering employees if the division of work is extensive, or centralizing distributed work within one organizational unit. Nowadays, several ideas from the field of AI inspire the redesign of business processes, namely:

1. *Optimization of business processes:* Ideas from the field of automated planning and scheduling are used to improve and optimize business processes, e.g., calculating optimal paths in business processes [18], or using non-deterministic planning approaches [14]. Exact quantification of such approaches is often unclear.
2. *Automatic adaptation of business processes:* Additionally, approaches from the field of automated planning are used to adapt business processes to new requirements automatically [50], e.g., the process scheme is changed to meet particular requirements.
3. *Trace completion and repair:* Other approaches follow the idea of using AI to automatically complete or repair process traces, as, for example [20], e.g., if a trace does not conform to the process model, then the necessary changes are made to ensure compliance. This might be useful under several circumstances, e.g., partially

observable process environments or noisy data acquisition.

3.1.4 Process Implementation

The organizational and technical implementation of processes is of major importance. AI particularly supports the automation of processes. Such solutions are very heterogeneous, but can be summarized as follows:

1. *Robotic process automation (RPA) and (cognitive) processes agents:* Agents are used to support routine activities in business process executions. In thcis context general potentials and challenges of using cognitive agents in process automation have been investigated [5, 19, 82]. Typically and foremost, these scenarios rely on software robots. However, as discussed before, sometimes RPA covers also physically robots [27].
2. *Support for knowledge-intensive processes:* Several techniques from the field of AI are not used to fully automate business processes, but to support or to assist the execution of business processes. For instance, process assistance can be improved by providing support from an ontology [49], machine learning can be used in complaint management in medical scenarios [32], or intelligent process support can be provided in customer services [46].
3. *Service-oriented architectures (SOA):* Additionally, autonomous agents are used in SOA. For example, in [42] an approach for the specification and execution of an agent environment in a SOA context is presented, e.g. the process model is used for the specification of the coordination of several agents.

3.1.5 Process Monitoring

During the process monitoring phase, huge amounts of data about the process execution can be collected and used for analysis. While classical approaches typically use just descriptive methods to provide some insights into BPM-systems, nowadays several ideas are developed to provide more sophisticated insights based on AI concepts and techniques:

1. *Process prediction:* The prediction of events before they occur based on obtained execution data from prior processes is a typical approach. In particular, predictions focus on next steps, the duration of a running process execution, expected anomalies or even on the identification of problems before they occur [21, 75]. Further work exists on the explainability of predictions [6, 30, 76], on benchmark evaluations [78], on deviation detection [37], on label ambiguity [57], on the generalization ability of next-activity predictions [1], and on the entropy analysis [8].
2. *Process alignment and log quality improvement:* Several ideas have been proposed for using AI to align different processes [9] or to improve the quality of event logs [29]. For instance, an adequate mapping between two process models is automatically derived.
3. *Visualization of running processes:* To improve the visualization of running process instances, techniques from the field of knowledge representation are used. For example, data and workflow descriptions are semantically-enriched to provide better insights into the running processes of a BPM system [61].

3.2 The Perspective of Artificial Intelligence

3.2.1 Natural Language Processing (NLP)

Techniques from the field of NLP are typically used in all phases of the BPM lifecycle [48, p. 9ff]. In particular, to understand and to describe a business process, a modeling language is used. Sometimes, business processes are just described with natural language, sometimes more formal concepts are used. However, even if only a fully formalized modeling approach is used, a natural language is necessary to interpret the concept of the formal framework—otherwise the process descriptions would not be understandable by ordinary domain experts. Hence, NLP provides several interesting potentials in BPM, namely:

1. *Parsing and annotating elements of a business process model:* Elements of a business process model are typically annotated with natural language labels, e.g., “process order form”, “customer order received”, “invoice checked”. NLP-methods such as part-of-speech tagging, or named entity-recognition can be used for annotating labels [48, p. 49ff.], [47]. This information provides new insights into process models.
2. *Naming conventions:* The naming of elements is often prescribed by some more or less explicit naming conventions, e.g., activities should be described by verbs or events should incorporate information about the state of the system [10]. Such rules can be detected and corrected by NLP techniques [48, p. 81ff.].
3. *Generation of process descriptions:* More formal business process models can be transformed into natural text [48, p. 103].
4. *Generation of process models:* Process models can be automatically created from natural language [28]. One interesting question is how to incorporate domain knowledge or other unstructured documents [15, 56, 64].
5. *Process automation:* A better understanding of the natural language labels could be used to automate fur-

ther tasks in BPM. For instance, the automatic service derivation from business process models [48, p. 137ff.] allows to identify and define software services needed to execute a business process. Another example is the automatic analysis of customer tickets to detect prior solutions to known problems and support assistance [46, 79].

3.2.2 Knowledge Representation

Business process models typically represent the domain knowledge of an application domain. In other words, classical methods from the AI field of knowledge representation are of major interest in the field of BPM. However, there are at least the following major differences: first, the explicit representation of process knowledge is typically used by humans and not primarily by machines; second, in knowledge representation more formal techniques are commonly used, while process modeling typically uses less formal models that often do not allow to provide automatic reasoning or other formal analysis. Nevertheless, interesting work lies at the intersection of AI and BPM:

1. *Semantic modeling and knowledge graphs:* Concepts from the field of AI such as semantic models, ontologies, or knowledge graphs are used for business process representation. This idea is often described as "semantic process modeling" [69] and offers several application cases, such as a more comprehensive process visualization [61], explainable processes [11], activity recommendations [66].
2. *Representation of uncertainty:* Process models contain several aspects of uncertainty. Hence, ideas of integrating uncertainty in BPM are discussed in the literature, e.g., uncertainty modeling of workflows [83] or uncertainty modeling of declarative process models [24]. Such representation could improve process prediction and explanation performance.
3. *Improving the quality of process logs:* Other works use techniques from the field of knowledge representation to enhance the quality of business process logs, e.g., in [29] the accuracy and completeness of the flow of events in low-quality logs are improved. Improved log quality can enhance discovery of process models, the ability to predict the future state of a running process, and similar tasks.

3.2.3 Automated Planning and Reasoning

As mentioned before, typical approaches to the representation of business processes are not primarily interested in the formal representation of concepts, and hence the use of techniques from the field of automated reasoning is not high. However, several ideas emerged in this area:

1. *Automated planning of business processes:* Several works discuss to employ automatic planning for business process management [50]. Besides the general idea, specific solutions have also been proposed, such as process optimization in non-deterministic planning [14], workflow repair and enhancement [20], and further idea [34, 35].
2. *Automated reasoning:* Several techniques from the field of automated reasoning are used for particular BPM problems, e.g., for the analysis of resource controllability [83], reachability analysis of process models [38], process optimization [18], trace generation by abduction [16], ontology-based reasoning for process assistance [49].

3.2.4 Machine Learning

A typical BPM-system such as an ERP-system or a WFMS does not include a machine learning component and still such systems work very well without machine learning techniques. However, such a system typically contains lots of data about processes and their execution—thousands or even millions of different process instances and events are not unusual. This process data can be used to learn something about the BPM system. This general idea leads to smarter or more cognitive processes [82]. Furthermore, many other application of machine learning emerge in the BPM field:

1. *Prediction of the future of a running process:* Based on historical process executions, the future of a running process instance can be predicted [53]. Typical used methods are in general deep learning [32], (Graph) neural networks [21, 36, 37, 75], some kind of transfer learning [1, 43], or reinforcement learning [70].
2. *Automatic process matching:* A process matching describes a mapping between similar activities, events, resources etc. in two or more different process models. Matching different process models is an important task if several process models exist. Few works have investigated how to learn the mapping of different process models through machine learning, such as [65]. In particular, for this scenario, some challenges emerged,such as the Process Matching Challenge [7].
3. *Process data representation and feature selection:* While all the approaches mentioned before discuss some form of representation, some particular work discusses this explicitly, in terms for instance of data representation and feature selection [4, 36].
4. *Issues in machine learning:* Problems related to the application of machine learning to BPM data are also

discussed by existing works, as for example generalization [1, 57], data leakage [78], process foundational models [25, 62], explainability of machine learning models [6, 30, 76].

5. *Open datasets:* It is important to note that for many machine learning tasks datasets are publicly available. As well known datasets, these datasets are sometimes overused, although they provide good baseline for comparison and evaluation of research results. Typical datasets are provided in the context of the *BPI Challenge*, *Process Discovery Contest*, or the *Conformance Checking Contest*. Furthermore, software systems have been proposed to create synthetic data [16].

3.2.5 Computer Vision

Computer vision is a major discipline in the field of AI. The use of computer vision techniques in the field of BPM is currently low. However, some interesting research approaches were investigated in the past:

1. *Recognition of business process models:* Prints or even sketches of business process models on white boards are used to derive a formal business process model [81].
2. *Automatic process detection in cyber-physical systems:* Administrative processes in "white-collar" workplaces are a classical BPM application field. However, interesting applications exist as well in "blue-collar" environments in which cameras, sensors, or other interaction modalities can be used for BPM, as, for example, process detection with camera and sensors for enhancing worker assistance [44], or for detecting unusual movements [60]. Moreover, special datasets exist in the field of computer vision for such analysis, e.g., [17].

3.2.6 Robotics

Although there are some initial ideas on the usage of robots in the context of BPM, e.g., service robots in customer case processes, the link between and overlap of robotics and BPM is very low.

If the term robot is not only understood as a hardware robot but also as a software robot, the situation is different, since software robots play an important role in the area of so-called "robotic process automation" (e.g., [19]). Also, this term is heavily used in industry and there is an important software market for the so-called RPA solutions. However, the products available in the market typically do not use some more sophisticated concepts and techniques from the field of AI but are very simple rule-based systems combined with some screen scraping technology.

However, currently, there are many ideas to use software robots. An example is the idea of agentic BPM is intensively used for tasks that are typically done by a human, such as buying a product in a web shop [80], booking a holiday trip [74]. Another idea explores desktop automation work using workflow automation [85]. Compared to robots, the degree of autotomy, agency and intelligence is rather low.

3.3 The Perspective of Application Domains

3.3.1 Domain-Independent Research

Although BPM has strong ties to numerous application domains in the field of business, enterprise, or management software, many research approaches do not address particular application domains, e.g., they use just an abstract and general understanding of business processes.

In particular, the idea of a process-aware information system (PAIS) has evolved. The idea of a PAIS implies that the system has some understanding of the number and kinds of processes that are supported by the software. Typically, e-mail-systems and office packages such as word processing or tabular systems, do not have an understanding of the supported processes.

On the other hand, systems such as ERP-systems, workflow systems, ticket systems, and case management systems, have a very comprehensive understanding of the processes that are running in the IT system or are supported by the systems. Otherwise, such systems would does not make any sense.

In particular, the work at the intersection of BPM and AI is often in this sense domain-independent. Nevertheless, many work in the area of BPM and AI also addresses particular problems in specific application domains that are discussed next.

3.3.2 Application Domains

Typical domains which are used as application cases, evaluation scenarios or problem descriptions are:

1. *Administration:* Typical administrative workflows such as filing applications, processing routine decisions, processing orders, are supported by BPM systems. In particular, since these processes are often of high-volume, an intelligent automation is of particular interest, as RPA in the domain of public administration [41].
2. *Manufacturing:* Manufacturing processes are often very complex and exhibit physical tasks, e.g., production, assembly, production logistics, product routing, as well as cognitive tasks, e.g., quality checks. Hence, combining BPM and AI in this domain is very interesting [33, 44] For example, in [44] the automatic detection of business processes is carried out in a manufacturing environment.

3. *Medicine and (health-)care:* Similar to manufacturing processes, healthcare processes are very complex: several agents have to be orchestrated, and many different systems are involved, e.g., laboratory systems, patient systems, and others. Hence, many works are motivated by and evaluated in the healthcare [3, 11, 70] and medical [32, 68] domain.
4. *Banking and insurance:* Many processes in banking and insurance are historically paper-based processes and are nowadays digitalized. Nevertheless, compared to processes in the field of manufacturing and healthcare, processes in banking and insurance often just deal with information objects and thus can be automated with software without using tangle robots. At the same time, this offers interesting application cases, e.g., for mortgage decisions, for processing of insurance claims [24], as well as for insurance settings [56].
5. *Service engineering:* As said before, the use of ticket systems is often assumed. This offers interesting proposals for automatic routing of tickets or analysis of incidents in service management processes [31, 46, 58].
6. *Other domains:* Several further application domains are investigated, such as e-mail [43, 64] and software development [15].

4 Discussion and Further Research Challenges and Opportunities

The discussion of the body of knowledge at the intersection of BPM and AI, together with further research opportunities will be carried out from three different facets:

1. *Theoretical facet:* What are the theoretical foundations of the field?
2. *Methodological facet:* How is knowledge in the field discovered and justified?
3. *Empirical facet:* What happens in practice when BPM and AI are applied in the real-world?

4.1 Theoretical Facet

As said before, the representation of processes lies at the core of BPM and knowledge representation is a core field of AI. Hence, many interesting theoretical questions occur:

1. *Core concepts/process representation:* A process can be understood in different ways. What is difference between a process instance and a process schema? How to deal with implicit knowledge in AI? How to define borders and interfaces of processes? How to represent a process in a computer (by a graph structure)?
2. *Causality:* An important question is how to represent causality in process models and executions. It is evident that a process evolves over time. However, the evolving time is typically not the cause for the evolving process. A placative example: A soccer match scheduled at 8 pm does not start when the clock hand jumps to 8 o'clock, but when the referee blows the whistle. Although many ideas exist to deal with causality of events in processes, a well-accepted foundation is still needed.
3. *Integration of explicit and implicit knowledge ("hybrid approaches"):* Currently, much of the data is used to represent knowledge, e.g., LLM, LxM etc. The term foundational model emerges. These concepts provide implicit representations of processes. However, in BPM, explicit rules are often of major importance, e.g., compliance rules ("four eye principle") or business rules ("an order is only processed after the payment is received"). Hence the interesting question emerges of how such hybrid knowledge can be used: what is the role of sub-symbolic process knowledge?
4. *Agentic BPM:* In the context of BPM, the idea of using agents is present. Currently, RPA uses only very simple techniques. However, in the future, much more sophisticated agents will emerge, which autonomously learn about processes, plan processes etc.
5. *Explainability and trustworthiness:* Both aspects are currently of major importance in the field of AI in general. However, especially in the context of BPM, several challenges are still open.
6. *Automated detection of processes:* Some first attempts at the instrumentation of the environment for the automatic detection and analysis of processes already emerge. In the future, such environment will get more importance. In particular, such an integration might be very seamless with more sensors and actors that use videos and many more context factors.

4.2 Methodological Facet

Historically, research on BPM focuses on more or less evident and practical cases on the one hand and on the other hand, formal proofs of important theorems in BPM, e.g., proofing the soundness of business process models [71]. In the future, during the research cycle, many more facets will gain importance, namely:

1. *Design-oriented versus empirical and behavioral research approaches:* On the one hand, the development of new concepts, methods and tools, is necessary. However, the usage and adaption in industry is also important. Hence, the engineering part is also necessary.

2. *Laboratory versus field studies:* BPM and AI research must find its way from the laboratory to the field. In the field cases studies alone are not acceptable.
3. *Application-oriented versus basic research:* BPM and AI research will focus on application problems, as well as foundational problems. Therefore, the integration of different approaches is necessary. Also, BPM-systems will not be fully automated. Hence, "human-in-the-loop" will be of utmost importance.
4. *Reproducibility and open science:* As long as research deals only with formal proofs of important theorems, the reproducibility and openness of research results are, to greater or lesser extent, assured. However, the movement to more empirical and engineering approaches, as well as research settings in the field, will open questions regarding transparency and reproducibility of results. The idea of open science did already emerge in the field of BPM.

4.3 Empirical Facet

Empirical research in BPM has a long tradition [39]. Clearly, more research results are needed to comprehend how well the theoretical understanding of processes and analysis techniques aligns with process management in the real world. This highlights the need for new kinds of interdisciplinary research that integrate human and machine behavior.

Particularly in the field of AI, the PEAS approach [63] is one idea to understand agent-based systems, namely:

- *Performance:* Which measurements are used to evaluate the performance of a system? From a business perspective accuracy of the solution, cost and time are all relevant measures.
- *Environment:* In which environment does the BPM agent work?
- *Actuators:* Which actuators are used?
- *Sensors:* Which sensors are used?

Currently, many AI-based BPM concepts, methods, or systems are analyzed based on an ad-hoc conceptualization of empirical research, e.g., without deep theoretical understandings or robust empirical phenomena. In the future, empirical studies should be designed around these ideas to really get a comprehensive understanding.

5 Conclusions and Outlook

We are currently living in a time, where the term AI is often used as a major buzzword in everyday communication although there is a well-known understanding of the field in academia. Our survey traces important lines of interrelationships between AI and BPM. From our perspective it would be more than necessary to better integrate the different streams of work.

Again, we like to point out that Herbert Simon was one of the great colleagues who shaped the field from both sides, namely the economics and artificial intelligence [54, 55]. In the future, we see one major line of possible integrations of both research fields: the development of robots, agents, and other forms of agentic systems, can, on the one hand, be understood as a basic building block for economics—for example Acemoglu et al. [2] define the market as a composition of different agents—-and, on the other hand, an agent is the major building block for an AI system [63].

For understanding software and economical agents we need a better understanding of the architecture of the systems, the dynamics, and the data. In other words, we need a comprehensive understanding of processes in which agents are living in the digital world.

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