DOI: 10.2195/lj_Proc_jacobi_en_202012_01
URN: urn:nbn:de:0009-14-51439

Maturity Model for Applying Process Mining in Supply Chains: Literature Overview and Practical Implications

Reifegradmodell zur Anwendung von Process Mining im Supply Chain Management: Literaturübersicht und Implikationen für die Praxis

Christoph Jacobi [1]
Mathias Meier [2]
Lutz Herborn [1]
Kai Furmans [1]

[1]Karlsruhe Institute of Technology (KIT)
Institute for Material Handling and Logistics (IFL)

[2]Barkawi Management Consultants GmbH & Co. KG

Logistics and production systems are confronted with a highly volatile business environment, a situation which increasingly pushes common supply chain analytics approaches to their limits. Process mining is an emerging technique to provide insights into business processes as they are being executed. However, the application of process mining in cross-organizational context has not been conclusively researched. In a literature overview, we review a set of 34 papers on the application of process mining in supply chains and classify them according to a three-stage maturity model. We find the majority of academic publications (28 papers) to focus on the construction of cross-organizational process models, 5 publications to derive models for alerting deviations and recommending decision support, and 1 paper to focus on automatic adjustments of the system behavior. Based on these findings, we conclude that the exploitation of process mining will be a key competitive advantage in supply chain management in the upcoming years. This applies not only for the design and management of steady-state supply chains, but also for the rapid adaptation of new solutions in transient systems.

[Supply Chain Analytics, Cross-Organization, Inter-Organization, Event Log, Steady-state Systems, Transient Systems]

Logistik- und Produktionssysteme sind mit einem äußerst volatilen Geschäftsumfeld konfrontiert, eine Situation, die die gängigen Ansätze der Supply Chain Analytics zunehmend an ihre Grenzen stoßen lässt. Process Mining ist eine neue Technik, um Einblicke in die Geschäftsprozesse zu gewinnen, während sie ausgeführt werden. Die Anwendung von Process Mining im organisationsübergreifenden Kontext ist jedoch noch nicht abschließend erforscht. In einem Literaturüberblick werden 34 Veröffentlichungen über die Anwendung von Process Mining im Supply Chain Management vorgestellt und nach einem dreistufigen Reifegradmodell klassifiziert. Die Mehrzahl der Publikationen (28 Veröffentlichungen) sind auf die Erstellung organisationsübergreifender Prozessmodelle konzentriert, 5 Veröffentlichungen stellen Modelle zur Warnung vor Abweichungen und zur Empfehlung von Entscheidungshilfen vor und eine Veröffentlichung beschreibt die automatische Anpassung des Systemverhaltens. Auf der Grundlage dieser Erkenntnisse wird geschlussfolgert, dass die Nutzung von Process Mining in den kommenden Jahren ein entscheidender Wettbewerbsvorteil im Supply Chain Management sein wird. Dies gilt nicht nur für die Gestaltung und das Management von stationären Lieferketten, sondern auch für die schnelle Anpassung neuer Lösungen in transienten Systemen.

[Supply Chain Analytics, Organisationsübergreifend, Ereignisprotokoll, Eingeschwungene Systeme, Transiente Systeme]

1 INTRODUCTION

Logistics and production systems are confronted with a highly dynamic business environment: The product variety is increasing, while orders to be fulfilled are getting smaller, but more frequent. Additionally, companies have to fulfill the demand for increasingly heterogeneous products with increasing number of variants and declining expected delivery times, but raising expected delivery reliability. Due to this business complexity, existing approaches for supply chain optimization cannot design, operate, and evaluate an agile supply chain effectively [JBD08], and although an enormous amount of data is available [San16], known approaches for supply chain analytics are reaching their limits.

In such an environment, only organizations which fully comprehend their processes while being able to quickly re-design them when needed, are able to remain profitable. Consequently, being aware of both, the actual logistic and manufacturing processes and the deviations from the planned process is essential for companies, in order to gain additional flexibility [BaS03].

Process mining is an emerging technology to support these efforts. Process mining aims to discover, monitor, and improve business processes by extracting knowledge from event logs [Aal11a]. The advantage of deploying process mining techniques is that decisions are based on real, observed processes and business behavior, not on assumptions or simulations. While process mining is already successfully applied within organizations, deploying system event logs on transactional level in cross-organizational applications (as it is the case for logistics processes in supply chains) is still of research interest: Which are the conditions and requirements to sustainably apply process mining in supply chains? How can the extracted process models be exploited to better design processes across organizations? How sophisticated are process mining techniques in context of supply chains and what are potential future research fields?

In this article, we introduce a three-level maturity model for the application of process mining in supply chains. Given this framework, we review and classify the current state of the art of process mining in cross-organizational context with focus on logistics and manufacturing processes. Finally, we discuss practical implications of our findings.

The remainder of the article is organized as follows: Chapter 2 gives a brief introduction into enterprise information systems and derives the shortcomings of conventional supply chain analytics approaches. In Chapter 3, we describe the methodological background of process mining, and introduce our maturity model. In Chapter 4, we review and classify the academic literature on the topic into the maturity model. In Chapter 5, we discuss the practical implications of our findings and conclude the article in Chapter 6.

2 DIVERSIFIED ENTERPRISE INFORMATION SYSTEMS

Supply chain planning and execution is based on a 60-year-old deterministic planning paradigm. Planning parameters which are subject to stochastic fluctuations (e.g. lead-time, prices of raw material, and expected machine capacities) are managed in an enterprise software systems as deterministic parameters. In contrast to the past, when supply chain planning was subject to simpler and more stable conditions, the complexity and uncertainty of supply chains heavily increased during the last decades. Consequently, the assumption of deterministic planning parameters is heavily challenged today. To counteract this uncertainty, the IT landscape of enterprises considerably diversified. The large ERP vendors split the software modules according to a divide-and-conquer approach and develop a number of novel software modules which take over highly specialized subtasks in the planning and execution of supply chains.

2.1 DESIGN AND SUB-SYSTEMS

The core of all Enterprise Information Systems is the Enterprise Resource Planning (ERP) system. ERP is the "system of records" [Joh14] of an enterprise, providing a consistent data basis and managing the master and transaction data of the enterprise. ERP is an enterprise-wide information and execution system [KGG11] which is exploited to effectively plan and manage all resources of an enterprise [KGG11]. By integrating different business functions in an organization (such as inventory control, procurement, distribution, finance, and project management) [TYB02], ERP aims to improve internal efficiency of the enterprise. Consequently, ERP is considered the most imperative information technology infrastructure in modern organizations [PaK05].

Increasing competitiveness and new business requirements in supply chains triggered the demand for integrated information systems and have made ERP vendors to develop additional modules of ERP [KGG11]. Essentially, the entity of software system, referred to as ERP-II [Mol05], offers a modularized ERP system, which is web-based and provides full collaboration in the supply chain [KGG11]. The aim of ERP-II is to pursue inter-organizational collaboration, extending traditional ERP which offered intra-organizational process efficiency [KGG11].

Several components, such as SCM, CRM, or SRM may be integrated. For example, supply chain management (SCM) systems provide information such as where the product is to be produced and the procurement of parts and delivery schedules. Customer relationship management (CRM) systems facilitate the managing of a broad set of functions which primarily include the customer identification process, and customer service management and supplier relationship management (SRM) enables the enterprise to manage its supplier relations in their entire lifecycle [Mol05].

In order to achieve a holistic optimization of the supply chain, requirements, capacities and materials in the procurement, production and delivery process must be planned simultaneously, a task ERP is not capable of [KuH02]. For this purpose, Advanced Planning Systems (APS) are deployed. APS were enabled by refining the mathematical programming models and in particular the genetic algorithms applied to solve the network problems of an entire supply chain. APS facilitate the central management of the supply chain activities and processes in real time, essentially by extending the MRP-II planning concepts to encompass the entire supply chain, and as a result the systems in effect are SCM systems [Mol05].

Although ERP already takes over important functionalities as an execution system, these are only directed at the internal focus. To compensate for these deficits, Supply Chain Execution Systems (SCES) are exploited. SCES take over tasks from warehouse, transport, production and order management with the aim to cover the time lag between planning and execution [FMW05].

2.2 Supply Chain Analytics

It is widely accepted, both from the academic community and from practitioners, that information from supply chain data is of high importance for an effective and competitive supply chain [AsM20]. After integrating ERP (e.g. with modules such as CRM or APS), companies may take advantage of advanced forms of supply chain analytics [AsM20]. In this context, analytics is defined as “the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions.” [DaH07] In isolated tasks (e.g. the forecast of retails [AQS01] or demand and supply matching [TCC17]), supply chain analytics approaches are applied successfully.

However, despite all the potential benefits of exploiting enterprise data in supply chains, [JoH16] find the benefits promised of Big Data Analytics (BDA) in supply chain planning were not realized in practice. Although companies invested in integrating Enterprise Information Systems, the investment has not led to a competitive advantage [BVL18]. Furthermore, [Cap16] reports only 27 percent of international organizations to consider their BDA efforts to be profitable. [AsM20] conclude current research to fail considering the context, failing to be actionable for practitioners, and academics to develop methods that are not relevant for practice. It is therefore unclear how to unleash the potential benefits of supply chain data, in order to design and maintain more competitive supply chains [AsM20].

3 Methodological Background

The problem so far is that exploitation of supply chain analytics has only led to the digitization of data, but not to the digitization of processes [Aal16]. Although enterprise information systems are increasingly “process aware”, little attention is devoted to process monitoring and process improvement [AaW04]. We therefore believe it is insufficient to analyze data without process reference, but instead necessitate the understanding of the processes in supply chains across the enterprises involved, in order to make sustainable and profitable decisions about the design and optimization of supply chains.

3.1 On the Importance of Process Mining

This assumption is supported by the increasing importance of the vendors of process mining software: Celonis, the world market leader in process mining, was valued at around EUR 2.5 billion in 2019, which is more than doubled within a year [HKM19]. Despite their efforts, vendors of process mining software have opened up hardly one percent of a global market estimated at EUR 40 to 50 billion [Mag20].

Process mining is considered an emerging technology in European and US enterprises: [Abb20] conducts a survey of 400 senior directors, managing directors, and C-level professionals from organizations with at least 50 employees in the US, the UK, France, and Germany from six industries (including logistics, transportation and distribution). They find 65 percent of companies to currently use, or being in the early stage of adopting process mining. [Abb20] concludes that companies realize the need for better insights into business-critical and customer facing processes: Companies being passive in understanding their processes risk operational inefficiencies and poor customer experiences.

[RoH20] conduct a similar study with 120 managers from Germany, Austria, and Switzerland in companies with an annual turnover of more than EUR 1 billion. [RoH20] conclude process mining to currently be a niche topic with, however, rapidly growing importance. In less than half of the surveyed companies, an implementation of process mining projects is planned or already initiated. However, more than 60 percent of the companies surveyed attribute great importance to this topic for the coming years.

In the academic research, process mining has been of interest since 2001 and yields convincing results in various application cases. Reviews can be found for the application of process mining in healthcare context [RoC19], application scenarios for process mining in various industry sectors [TFB18], and with focus on the realization of business value from process mining [EgH20]. Process mining has been successfully applied in various intra-organizational problems [ARW07], the challenges of using supply chain event logs that span different companies are, however, not conclusively researched so far.

3.2 Theory

Process mining is a BDA technique aiming at discovering, monitoring, and improving real business processes and provides an important bridge between data mining and business process modeling and analysis [AAA12]. Starting point is an event log, which stores a list of evens, each referring to a process instance (case) and an activity. Events are ordered chronological and additional properties (e.g. timestamp or resource data) may be present [AAA12]. The event logs typically stem from process-aware information systems such as workflow applications or ERP systems [InG08], customer relationship management systems (CRM) or workflow management systems (WfMS) [AWM04].

Process mining extracts information from the event logs to capture the business process as it is being executed, rather than building the process model theoretically [AaW04]. These process models will then be represented in Petri nets (or similar graphical representations, e.g. UML or hidden Markov models) [AAA12]. Three types of process mining can be distinguished [AAA12]: In the *discovery* phase, the process model is constructed on the basis of event logs without using any additional a-priori information. An existing process model is compared with the event log of the same process in the *conformance* phase. In the *enhancement* phase, an existing process model is extended or improved by using information on the actual process recorded with event logs.

3.3 PROCESS MINING IN SUPPLY CHAINS

When different organizations construct process models of their joint operations, this is called cross-organizational process modeling [BoA11]. We identify three types of cross-organizational cooperation: Cooperation between legally separate organizations, cooperation within one legally coherent organization that has grown inorganically, and cooperation in one legally coherent organization with independent entities (e.g. branches). Depending on the type of cross-organizational cooperation involved, some of the concerns described below will be more or less pronounced. However, in the following, we do not differentiate between these types of cooperation.

There is a great awareness that organizations need to monitor and optimize their businesses across the organizational boundaries [LeW07], [Ber08]. Manual construction of cross-organizational processes, however, is difficult and time-consuming since several people from different organizations have to put together their partial knowledge of the overall process, and the running event log of the workflow is usually distributed on different severs owned by different companies [AWM04]. This is especially the case for logistics processes, which are characterized by a high number of frequently changing organizations involved in a supply chain as well as the variety of goods handled and services offered. On the one side, this dynamic behavior necessitates well documented processes. On the other side, it complicates sustainable process documentation and optimization. However, since the identification and tracking of goods in the supply chain is completely digitally documented, logistics systems have the opportunity to greatly benefit from process mining.

The deployment of process mining in cross-organizational context raises various questions, both in research and in practice. In supply chains, several organizations are forced to closely collaborate and to jointly handle process instances. Discovering end-to-end processes necessitates merging the event logs of different organizations. However, sharing information within the supply chain may be critical due to competitive reasons or lack of trust. In contrast to organization-internal deployment of process mining, cross-organizational process mining emerges problems related to confidentially, privacy, and data heterogeneity [Aal11b]. Further, the problem of compatibility and integration of information systems and processes is still a concern [BuM16]. Still, the vast majority of companies face significant discrepancies between the (envisioned) process specifications and the observed reality [KaS17].

3.4 MATURITY MODEL FOR APPLYING PROCESS MINING IN SUPPLY CHAINS

Today, the management of supply chains relies on the update of the data sources integrated in (near) real-time, and further, sufficient computing power is available to analyze events as they occur. Consequently, process mining should not be restricted to subsequent analysis, but can be applied for online operational support [AAA12]. To provide operational support using process mining, [AAA12] identify three activities: *detect*, *predict*, and *recommend*. In the moment, a case deviates from the process model, one can generate a notification immediately. Predictive models can be constructed using historical deviation data. Based on these predictions, a recommendation may be derived to propose particular actions.

Inspired by the insights derived from BDA and process mining, we derive our maturity model for the application of process mining in supply chains. Following the examples proposed in [AAA12], our model is composed of three stages and tailored, but not limited to the application of process mining in supply chains. We identify three activities for process mining in supply chains: *Construction* of cross-organizational process models, *Alerting* deviations and providing *Decision Support*, and *Automated Adjustments* of processes and decisions.

Just as in the discovery phase, *constructing* cross-organizational process models aims at building the process model to depict the state of the art. In contrast to common algorithms, additional difficulties arise from the fact that the data sources may be physically separated, and thus interfaces need to be defined, the data need to be merged, and converting of data types needs to be considered. Further, if the companies do not want to share their entire process model with partners and potential competitors, construction algorithms of cross-organizational process models need to maintain privacy.

Given the cross-organizational process model, process mining algorithms may be exploited to detect deviations and raise an *alert* and to provide *decision support*. We differentiate an optimization from a stabilization effect:

Deviations may occur in and be detected for both, the data and the process model. For example, defective data may be incorrect product information (e.g. an incorrect price or delivery date), discoordination between the partners (e.g. defective value for lead time), or sensor faults (e.g. inventory mismatches in ERP and warehouse). The occurrence of these errors can be detected through a comprehensive process analysis and necessitates to adjust the control parameters in the IT systems. After integrating statistical analysis methods, the process model provides a recommendation as to which value the parameter should be adjusted to.

Deviations in the process model include product routing errors (e.g. shipping to the wrong customer), missing log data (e.g. due to server hardware faults), or human mistakes in manufacturing or inventory management (e.g. picking an incorrect part number). If the running process is executed on a branch that has caused problems (e.g. delivery time delays) in previous executions with a given probability (e.g. 95%), an alert is issued. By establishing this transparency, it is possible to respond to problems at an early stage, for example by re-planning the production sequence. Advanced analysis methods may recommend appropriate interventions, or allow the impact of different alternatives to be predicted.

After integrating further technological developments, such as prescriptive analytics, artificial intelligence, machine learning or robotic automation, the process mining technique may not only provide decision support, but to *automatically adjust* the deviation. The deviations occurring in reality are detected by the process model and counteracted by the integrated decision techniques, so that the supply chain becomes a self-regulating and self-controlling system. Consequently, this situation does not necessarily involve any human decision-maker, and the technology can be considered as fully autonomous digital twin of the supply chain.

4 Literature Review

We conduct a literature review which is based on the results described in [JCS18]. The Systematic Literature Review (SLR) method is used in [JCS18] to review a collection of twenty-one papers regarding cross-organizational process mining approaches in supply chains published between 2001 and 2016. [JCS18] present a clear and structured overview on the topic and focus of providing meta information of the literature, whereas the contents of the publications are only marginally discussed.

With our literature research, we extend the collection of literature presented by [JCS18] to 34 papers published until 2020 and aim to provide insights into practical implications of process mining in supply chains. In the following, we present the results of our review and classify the papers found according to our maturity model.

4.1 Construction

We find 28 papers with respect to construction of cross-organizational process models. Out of this set, 3 papers describe fundamental definitions and requirements for applying process mining in cross-organizational context, 4 papers address the problem of privacy preservation, and 3 papers are concerned with performance of cross-organizational construction of process models. Although data is reported to be “readily available in today’s systems” [Aal11a], this is actually not the case in many cross-organizational process mining projects. Therefore, 11 papers address the problem of technology and software integration, and 2 papers describe the integration of cross-organizational process mining with blockchain technology. Finally, 5 papers report applications of cross-organizational process mining and describe case studies.

4.1.1 Definitions and Requirements

With *collaboration* and *exploiting commonality*, [Aal11b] considers two basic settings for cross-organizational process mining. In a collaborative setting, different organizations work together to jointly handle process instances. Collaborations are divided into:

- Capacity sharing: The routing of case is under the control of one organization, while the execution is distributed.
- Chained execution: The process is split into disjoint sub-processes, which are executed by organizations in sequential order.
- Subcontracting: Sub-processes are subcontracted to other organizations.
- Case transfer: Each organization is capable of executing the process. Each case, however, resides at exactly one location.
- Loosely coupled: The sub-processes are defined locally, that is, there is no organization which needs to know the entire process.

In a setting of exploiting commonality, different organizations aim to learn from each other or to share a mutual infrastructure, while essentially executing the same process. For example, municipalities offering the same service to the citizens are interested in sharing an infrastructure (e.g. IT) and sharing experiences. Furthermore, [Aal11b] differentiates *horizontal* and *vertical* partitioning: In horizontal partitioning, the process is split into parts and each fragment of the overall process is under the control of one organization. In vertical partitioning, cases are distributed over several organizations each using their own variant of the process.

[Aal00] focuses on loosely coupled cross-organizational workflows and addresses the problem of cross-organizational workflow construction and verification. After defining properties for consistency, [Aal00] introduces an analysis technique to verify the validity of a cross-organizational work flow, which is also implemented in a software tool. Given a cross-organizational process model, the algorithm is able to determine basic properties, such as the absence of deadlocks and livelocks in Petri nets depicting cross-organizational processes. Given the communication structure (that is, the protocol of the partners in a supply chain), [Aal00] extends the algorithm presented for the efficient verification of consistency with the process model.

In order to discover process models in supply chains, [MWW03] define requirements for the deployment of process mining techniques: First, each partner involved has to enable task registration to allow recording all tasks or activities which have been executed in the process. Second, the partners especially have to agree on common order and quotation numbers for the same type of process. Given these requirements, [MWW03] present two heuristic methods for discovering process models in supply chains and inducing Petri nets for process representation. However, when applying these methods in practical situations, [MWW03] identify the problem of noisy workflow logs (due to missing registration data or input errors), to yield incomplete business process models. Despite these limitations, [MWW03] conclude that supply chain activity can be improved when partners benefit of a deeper understanding of the entire distributed process.

4.1.2 Privacy, Trust, and Security

[CKL02] detail how to model composite E-services as cross-organizational workflows. An E-contract can be briefly described as an abstraction of an agreement between two or more parties in which the parties agree on a task assignment in a shared process. [CKL02] present a methodology to define and verify an E-contract and develop an advanced cross-organizational workflow environment for cooperation with other organizations over the Internet for E-service enactment. Finally, [CKL02] raise the question of trust and security: In order to cooperate, each party must be able to view at least a subset of the other party's workflow which specifies the tasks obliged to perform, while maintaining the privacy of other unauthorized information. For example, customers may want to check the progress of order process, but the contractor must not pass on internal information, e.g. whether the order has been post-processed. In the workflow view mechanism proposed by [CKL02], each partner specifies a view of its internal workflow which is accessible to the other parties.

[LDZ16] also address privacy-preservation in cross-organizational business processes for both, the event logs, and the process model itself. [LDZ16] propose a framework to handle privacy which includes that:

- Each organization discovers its private and public business process models in event logs,
- A trusted third-party midware takes the public process models as input and generates cooperative public process model fragments of each organization, and
- Each organization combines its private business process model with its relevant public fragments to obtain the organization-specific cross-organization cooperative business process model.

[LDZ16] transfer the framework to algorithms for mining cross-organizational cooperative process models based on Petri nets.

[ISV15] present a privacy-preserving business process recommendation and composition system. The system generates a differentially private dataset of execution sequences which can be published and shared with other organizations for composition and implementation of their business processes. For this purpose, [ISV15] exploit the sequential composition property of differential private computations by modeling the execution sequences as a graph and performing random walk on this graph in order to generate comparable execution sequences which cannot be linked to a contributing organization. With this approach, privacy can be preserved if an executable business process has to be composed based on the knowledge of existing business processes, as it is the case when creating business processes which utilize existing web services.

[ALG17] address the problem of modeling cross-organizational processes out of the private process models of the organizations which aim to collaborate. [ALG17] present a set of process adaption patterns to connect private process models: By deploying a process mining approach, the private processes are analyzed and interoperability issues are identified. To resolve interoperability issues identified, a process adaptation patterns specification is proposed. Finally, the identified patterns are applied to adapt the private processes and build a single cross-organizational process.

4.1.3 Performance and Efficiency

[Gor19] presents a supply chain topology model in order to improve its overall efficiency. The focus of optimization lies on cost and material management for participants, while at the same time maintaining flexibility: If, for example, the delivery along the standard path is not possible, another supplier or distribution path should be selected without significantly rising costs. [Gor19] raises and discusses various questions for further research, including selection of tools and techniques for supply chain model building, collection of necessary data, choosing effectiveness measures, model verification, and results evaluation.

[HaS19] investigate the performance of five automated process discovery techniques within a controlled simulation environment of the logistics processes in a manufacturing company. For performance evaluation, [HaS19] choose fitness (that is, the ability of the model to reproduce behavior contained in the log), and precision (the ability of the model to generate the behavior present in the event log) as performance measures. [HaS19] find discovery algorithms to overall perform better, when using more extensive event logs both in terms of fitness and precision. However, when the process models are less complex, the algorithms are found to perform better with smaller data sets. Latter phenomenon is amplified through integration of the supply chain within Industry 4.0 and should be considered especially by companies with long delivery cycles, long processing times, and parallel production.

[PKB17] consider the co-existence of multiple variants of the same business process within similar organizations. Common process fragments may be extracted from the repository of the process models during the design phase in order to significantly accelerate the design process. [PKB17] investigate the use of ontological theories for the theoretical analysis of process fragments and propose *morphological fragments* to support composability and flexibility. Further, [PKB17] present an algorithm for extracting common morphological fragments from a collection of event logs, and a supporting algorithm for clustering fragments based on a degree of morphological similarity.

4.1.4 Technology and Software Integration

To make supply chain data accessible for process mining, [GCM09] propose to use RFID events. Since Electronic Product Code (EPC) information (which uniquely identifies each product) are processed, there is no explicit notion of a case identifier that groups events belonging to the same process instance and thus, RFID events cannot be used directly for process mining. To make process mining applicable, every event has to be assigned to a process instance. Using EPC as a process ID does not work, however, due to the problem of various packing and assembly operations during the process. The shipper of a product may pack cartons on a pallet and pallets into a container, which might prevent reading the RFID tags attached to the products. Thus, the focus shifts from the single product to the container. By tracking aggregation and transformation during the process, [GCM09] derive an algorithm of mining supply chain processes based on EPCglobal events. In a simulation study, [GCM09] validate coherence, quantities, and transition reliability of the mined processes.

In order to make use of process mining in supply chains, enterprises need to share event logs and transactional data. However, system vendors may record and describe the events according to their own standards and languages [DoA05]. To overcome this problem, [KLK09] present a generic data model to extract process trace data from event logs stored in SAP NetWeaver, which provides a facility for integrating SAP and non-SAP systems.

[CMJ07] present an ontology for integrating UML methods with XML nets for design, execution, and monitoring of cross-organizational business processes. UML is a standard modeling language, which supports business processes acquiring for both professionals, and non-professionals. However, UML lacks of dynamic analysis, verification, and precise formal semantics capabilities. By integrating UML with XML nets (which is an advanced variant of Petri nets), [CMJ07] support all activities in Business Process Management: Since XML nets are machine readable, the process can be designed automatically. When executing XML nets in the workflow engine, the process can be executed. Finally, after defining process indicators, the process is automatically monitored.

[SZW11] propose to apply process mining techniques in the fragmentation of workflows for distributed execution. Since workflow systems are typically build upon a client/server architecture, which uses a single server to manage the operations of an entire process, decentralization of workflow applications in distributed workflows on several servers improves the efficiency of the workflows systems and provides scalability for cross-organizational workflow management. Based on the discovered process model, [SZW11] determine the minimum server resources required for distributed execution and present an algorithm for the fragmentation of the workflow in order to achieve efficient server usage.

In cross-organization context, multiple data sources are often integrated to adopt “Big Data” techniques to extract statistics or other latent information [AzC13]. Data integration, however, requires different parties to agree on a common model and to provide a uniform interface to query the different interconnected data sources. [AzC13] propose a semantic lifting approach (that is, all transformations of low-level systems logs carried out in order to achieve a conceptual description of business process instances) to process distributed data, especially tailored for process mining algorithms.

When using cloud computing, organizations executing the same process can benefit from converged infrastructures and share information about how different variants of the process are executed. [BCM14] present a cloud computing multi-tenancy architecture with systematic extraction and composition of distributed data into coherent event logs, and the integration of online process mining techniques for the extraction of business rules. These business rules provide a way to represent complex behavior under an “open world assumption” where everything is allowed until it is explicitly forbidden. As a result, users can monitor the process variants at runtime and continuously improve the cloud control and its architecture, e.g. by optimizing the allocation of the resources on the available nodes.

In [BCM18], the authors present an extension of the work described in [BCM14] which covers cross-organizational process mining in multi-tenancy cloud environments of different organizations executing the same process in different variants. The approach exploits contextual information (tenant id, node id, and trace id), which is later used to identify traces belonging to the same process variance. From the collected event logs, a set of business rules is discovered to represent the process variants running on the cloud infrastructure.

[ClP14] address the problem of merging historical recorded data for process mining in cross-organizational context. They differentiate three levels of merging: Raw data-level (i.e. databases), structured data-level (i.e. event logs), and model level (i.e. process models). Merging data at structured level seems appropriate for cross-organizational process mining because first, individual partners are responsible for selecting, structuring, and choosing the abstraction level (which is less convenient at the level of the raw data as recorded in databases), and second, the choice of the mining technique can be postponed. Consequently, [ClP14] present a rule-based algorithm with tool support to merge event logs of different sources in support of cross-organizational process modeling. Two consecutive steps are performed: First, the algorithm discovers links between two event logs to indicate which data in both logs is considered to belong to the same process instance. Second, based on the configured links, the algorithm merges the data of both events to form a new event log.

In differentiation to approaches merging event logs from different organizations on one server, [ZSD13] propose a process mining based integration approach to obtain cross-organizational workflow models, whose event logs are distributed in different servers located in different organizations. The event logs contain information on resource allocation and messages exchanged, which are two important coordination mechanisms between organizations. The concept is based on extended Petri nets which allow representations of resource allocation and message exchanged in workflows. By using this process mining approach, four coordination patterns (namely synchronized activities, messages exchanged, shared resources, and abstract procedures) between the organizations can be obtained. Additionally, [ZSD13] present a process integration approach for a cross-organizational workflow according to the coordination patterns.

[BeI17] investigate how to apply context awareness based on Machine Learning in process mining of logistic systems. They retrieve additional information from the event logs recorded, namely the frequency of occurrence of each sub-process (that is, visit of successive machines), and the stability of each sub-process (by calculating the coefficient of variation of cycle time). By applying k-medoids clustering algorithm, [BeI17] are able to group similar process variants together and thus support process discovery.

[KOJ20] introduce a process analytics framework to support process-oriented analysis, as well as data-oriented analysis. The framework consists of a business process environment including collaborative processes, a data storage of process warehouses and process cubes (generated from the event logs and their metadata), and an analysis environment using the process cubes through data- and process-oriented analytics tools. To analyze the performance of business processes, [KOJ20] present collaborative performance measures on the basis of SCOR-model, with the perspectives finance, partnership, collaboration processes, and growth. Finally, [KOJ20] present three applications of the framework in supply chain analytics: First, the process model is discovered, and second, operation performance is analyzed (applying data analytics techniques, such as classification for on-time delivery, and regression for design change rate). Finally, a decision tree classifier is deployed to predict performance measures such as completion time or costs.

4.1.5 INTEGRATING BLOCKCHAIN TECHNOLOGY

[TöT19] propose blockchain technology to be the gateway for the connection of processes and to deliver the relevant data for process mining. Blockchain technology supports cross-organizational process mining since external parties (e.g. suppliers, customers, auditors, or inspectors) can be integrated as equal partners which trust transactions stored in and verified by the blockchain. [TöT19] propose to exploit blockchain technology to bridge the gap between the IT systems of different organizations, and generating event data through the use of smart contracts. By evaluating the answers of 56 experts from industrial practice and process consulting in a questionnaire, [TöT19] confirm their hypothesis regarding process breaks between different IT systems. However, the idea of implementing blockchain technology in supply chains is seen critical: The experts identify impediments for implementation and the performance of mass data processing.

[KPT19] address the problem of applying process mining to smart contracts and present a framework for extracting and analyzing blockchain event data. For executing cross-organizational processes, blockchain technology is becoming increasingly important since it guarantees that all participants in the network agree on the states of transactional data. [KPT19] present a framework to extract event data from Ethereum's transaction log. The presented framework consists of three parts: The *manifest* is a meta-model which specifies how data are logged, the *extractor* applies the rules from the manifest and retrieves the data, and the *generator* produces logging code to support smart contract developers. In a case study, the implementation of the framework is demonstrated and validated.

4.1.6 Applications and Case Studies

[Li10] uses process mining to derive virtual organizations structure models from log data extracted from supply chain management systems (SCMS). Since the event logs contain information on the performers executing or initiating the event, the relation and collaboration of performers can be extracted. In this way, [Li10] compensates the lack of existing organizational structures throughout supply chains.

[EAZ12] uncover cross-organizational business processes of an automotive supplier company by analyzing Electronic Data Interchange (EDI) messages. Traditional EDI systems are typically solely responsible for sending and receiving messages and are thus “unaware” of the process. Consequently, EDI messages do not contain explicit case identifies to map individual messages to process instances. Therefore, [EAZ12] define specific data elements (such as order or shipment number) as identifier. In the next subsequent process step, however, the identifier may change (e.g. the order is shipped with a new number). Therefore, [EAZ12] develop an algorithm to identify overlapping correlators which are used to trace the interdependencies of individual EDI messages. Finally, [EAZ12] present the Heuristics Miner algorithm for mining the business process from the correlated EDI messages.

[EKZ16] address the shortcomings associated with usage of EDI technology, as well: Since EDI messages are widely used for collaboration in B2B business, but typically lack a notion of the process, systematic approaches for applying business intelligence and process mining methods are not available. [EKZ16] present a framework for the application of process mining techniques for EDI-supported cross-organizational business processes. In a case study, [EKZ16] evaluate the applicability of the framework for investigating cross-organizational business processes for a German consumer goods manufacturing company with its retail business partners. After defining the KPIs “Total revenue” (to measure financial performance), “Average revenue per customer”, and “Average ordered quantities per customer” (to measure customer satisfaction), [EKZ16] are able to derive in-depth investigations and correlate the business performance and customer satisfaction to observed problems (such as late delivery and late invoice). However, [EKZ16] conclude that deriving financial KPIs solely from EDI messages is insufficient and therefore including further data sources is necessary to extend the performance analysis.

[BDA12] propose an approach for the comparison of process models and process execution between organizations. Almost all performance indicators used in business process intelligence systems (such as average time required for a case to be processed, arrival rate of new cases over time, the share of waiting time in total time, average number of different activities per case) can be used as metrics to compare process models. Applied to cross-organizational processes of municipalities, [BDA12] demonstrate that even simple metrics (such as average throughput time) provide valuable insights for comparing organizations regarding “better” performance when both organizations share comparable process models.

[JSR19] detect the actual container movements in a port and measure the dwell time of logistics processes from arrival of the container at the port (unloading) to departure of the port (truck out). With this approach, [JSR19] are able to provide insights into possible process optimization by reveling the handling difference of the container with fastest dwell time (1 hour, 6 minutes), and median dwell time of all containers (5.5 days).

4.2 Alerting and Decision Support

We find 5 papers to present frameworks and algorithms according to alerting deviations and providing decision support. The publications are further clustered in Correlation Analyses, Business Process Monitoring, and Compliance Monitoring and Computational Auditing.

4.2.1 Correlation Analyses

[LHZ09] present an iterative process mining algorithm to analyze correlations between combinations of process parameters, and the degree of customer satisfaction. The objective of the algorithm is to identify the improvement actions for supply chain network optimization in term of fuzzy association rules. In a case scenario, [LHZ09] demonstrate how to identify root causes of the failure of products, based on the historical process data. In this example, [LHZ09] find suppliers’ lead time, quantity of material ordered, and fixture angle of the machine to be important parameters on customer satisfaction, which are indicated by delivery time and number of defective items. When applying their algorithm, [LHZ09] propose to identify the primary factors which have a great effect on customer satisfaction in a supply chain. However, the approach is computational expensive to identify significant association rules since it requires an enormous amount of data, but provide valuable managerial insights.

[RLM12] present a methodology, system architecture, and implementation of a Business Process Insights (BPI) platform for discovery, execution, and evolution of semi structured end-to-end processes. A semi structured process is defined as a process which may cross enterprise boundaries and whose execution is not coordinated by one single entity. To synthesize the process model, [RLM12] deploy correlation rules on the events which generate process instance traces. The process traces are then used to explore aggregate behavior of the process (by deploying process mining algorithms) or for training predictive models (such as decision trees) to make predictions on future behavior in real time. The predictions include the computation of the likelihood of tasks in a running instance, triggering alerts, and injecting actions into source systems in order to seize opportunities or trigger counter-measure to avoid risks.

4.2.2 Business Process Monitoring

[CVW13] propose an approach to flexibly design and enact cross-organizational business process monitoring based on Product-Workflow design. Since organizations strive for agility and flexibility, a common strategy is to focus on their core businesses, and engage in collaborations with partners to maintain and possibly improve the level of quality and cost-effectiveness. Collaboration, however, requires active control and monitoring, which should always support the passive method for coordination, established through contracts. [CVW13] present an approach for designing optimal business process monitoring which can be flexibly re-designed as the collaborations evolves (e.g. when processes are outsourced to new partners, partners are substituted, or new contracts are deployed).

4.2.3 Compliance Monitoring and Computational Auditing

[WHT18a] identify an immense integration gap between enterprise systems and compliance management systems, triggering massive manual efforts for controls, increasing redundancy, and errors (e.g. inaccuracy of goods descriptions, wrong claims of duties). To address this problem, [WHT18a] present a systematic compliance monitoring framework for regulatory supervision in supply chains, analyzing operational processes focusing on import and manufacturing. In the framework, process discovery aims to elicit the process model and compliance rules. The process model encodes all the sequences of activities that are allowed by the organization's information system and the compliance rules. The process model is then used to analyze event logs for conformance checking and for detecting possible deviations. Finally, the identified deviations are analyzed together with the stakeholders involved.

[WHT18b] propose a framework for the application of process mining to assist manufacturing companies and regularity authorities with computational auditing, based on fault taxonomy. Business process models are used to capture various logistics (e.g. movements in/out warehouse) and compliance recording processes (e.g. changes in compliance status of processes). [WHT18b] present a generic fault taxonomy for computational auditing and execute conformance checking in a case study with empirical data to automatically diagnose root causes.

4.3 Automated Adjustments

[BKM19] propose an architecture to model system-wide behavior by combining process mining with multi-agent systems (MAS). Supply chain environments (such as distributed control of manufacturing operations, or coordination and cooperation of logistic processes between independent supply chain actors) may be represented by an MAS. The agents then represent (virtual) entities of a supply chain, such as machines and IoT devices. [BKM19] propose agent-based modeling (ABM) and process mining to mutually stimulate business process improvements: agents can adapt and change their behavior, and update their strategies based on extracted knowledge from interaction with their environment. Event logs, and the discovered process models, act as a trusted source for the agents and provide a shared knowledge of the actual events, which is not based on conjectures or intuitions. Consequently, instead of designing a MAS which is robust to any type of disruption, [BKM19] propose to adapt the system and its behavior under changing circumstances so that the acquisition and analysis of event logs enable intelligent agents to act autonomously on emergent behavior. Intelligent agents, who automatically make decisions to fulfill their predefined interests and goals, and the application of the process mining tool to gain insights in both the individual agent performance and system performance thus form a synergistic interaction to analyze the impact of agent intelligence and evaluate the system-wide performance: An agent can update its perception based on the emergent behavior detected within the process models created and, as a response, adjust its behavior accordingly. Finally, [BKM19] present a simulation-based case study which considers the job-shop scheduling problem with automatic transportation between the machines by AGVs. [BKM19] find it to be beneficial for an agent (that is, a machine, an AGV, or a product) to modify its decision to improve overall system performance. For example, an AGV may select another routing priority rule based on a performance quality score (e.g. throughput time), provided by the process mining algorithm. [BKM19] conclude the continuous interaction between the agents to provide opportunities for optimal self-learning capabilities.

5 Practical Implications

Based on the results of our literature review, we discuss the practical implications of our findings. The focus of our discussion is twofold: We differentiate the application of cross-organizational process mining in steady-state supply chains from the application in transient systems.

5.1 Process Mining in Steady-State Supply Chains

In steady-state systems, the business processes of supply chains are confronted with known statistical fluctuations and uncertainty (for example, order quantity and delivery time are normally distributed with an empirically known variance). We identify a transparency and an optimization effect as an advance when applying process mining in these systems. Further, we discuss emerging problems resulting from process transparency.

By providing end-to-end process transparency of the entire supply chain, we expect to increase efficiency, responsiveness, and stability of logistics processes. Inefficiencies arising from local optimization efforts can be identified and eliminated. For example, companies (production plants, wholesalers, retailers) are typically decoupled by intermediate warehousing, which serves to compensate for stochastic fluctuations. Providing end-to-end process transparency may support decision makers to partially eliminate these inefficiencies and to reduce bullwhip effect.

Considering the results reported in [BKM19], we believe it to be beneficial to exploit process mining techniques for building an autonomous digital twin of the supply chain. After integrating prescriptive analytics tools, the digital twin may interact with its environment and extract domain-knowledge based on the analysis of the process model. The digital twin may autonomously adapt and change its behavior and update its strategies based on the deviations perceived and the consequences forecasted. Consequently, the transparency effect becomes an optimization effect, when all parties adapt their strategies and behavior decentralized and dynamically with the aim of overall process efficiency.

However, establishing an overall end-to-end process transparency in the supply chain may emerge a conflict of interests. Currently, supply chain management is characterized by a divide-and-conquer approach which results in local optimization and decoupling of processes. An overall (that is, "global") process transparency urges a global process optimization. Consequently, the partner of the supply chain must agree on the leading optimization criteria: Does the cooperation aim at a maximum utilization of machine and transport capacities, or should delivery reliability be increased? Is time, monetary or quality characteristics leading? The global optimum may only be achieved on the expense of individual partners of the supply chain (who, for instance, need to produce in a locally inefficient order sequence, or switch container management to prevent repackaging elsewhere). The resolution of this conflict will be left to negotiation of the parties based on the findings of game theory.

5.2 Process Mining in Transient Supply Chains

Unforeseen events beyond the known statistical fluctuations (e.g. the eruption of Eyjafjallajökull or the global Covid-19 pandemic) impose additional challenges on the management of complex supply chains. Unique catastrophic events lead to a shutdown of regional, or even global supply chains. In case of the Covid-19 pandemic, companies are confronted with temporally and regionally randomly occurring limitations or complete failures of individual production, transport and storage capacities. We call such a system, which is constantly confronted with uncertainty and continuously transitions from one unstable state to another "transient".

In such a situation, operational transparency of the supply chain may make the difference between economic survival and bankruptcy of a company: In contrast to steady-state systems, the management of a transient supply chain (e.g. order policy, payment, and delivery) necessitates abrupt real-time reactions and a comprehensive overview of the current status of all deliveries, orders, and contracts. A lack of overall process transparency may – in the worst case – delay the search for inefficiencies and short-term savings in a transient state, until the company is bankrupt.

6 Conclusions

Supply chain planning is based on a 60-year-old planning paradigm. As the business environment for logistics and production processes has become increasingly complex in recent decades, supply chain analytics approaches reach their limit and facilitate local optimizations. Process mining is a BDA technique to establish an end-to-end process transparency and yields convincing results in projects with company-internal focus. However, the deployment of process mining in cross-organizational context, and especially with focus on logistics and manufacturing processes in supply chains, is still of research interest.

We present a three-stage maturity model and identify *Construction*, *Alerting and Decision Support*, and *Automated Adjustments* as application activities of process mining in supply chains. Our maturity model is tailored, but not limited to cross-organizational applications of process mining. We classify 34 papers with focus on process mining in cross-organizational context according to the maturity model. From a technical point of view (privacy, data conversion, and merging), we conclude that there is nothing to hinder cross-organizational process mining in supply chains. Privacy, for example, may be abstracted by an algorithm or the type of data recoding such that business-relevant data (e.g. order or material number) cannot be traced back to that company.

By integrating process mining techniques with further emerging technologies for prescriptive analytics (such as Artificial Intelligence, Machine Learning, and Robotic Automation), we believe it to be possible to ultimately build a digital twin of a supply chain. By exploiting this digital twin, not only for monitoring and analyzing the supply chain, but also assessing the consequences of decisions in the future, we believe it possible to build a self-adapting and consequently self-healing supply chain with overall efficiency. Finally, we conclude process mining (and the resulting overall process transparency) to possibly mean the difference between the economic survival and bankruptcy of a company, when operating in a transient supply chain.

LITERATURE

[Aal00] van der Aalst, W.M.P.: *Loosely Coupled Interorganizational Workflows: modeling and analyzing workflows crossing organizational boundaries*. Information and Management, Vol. 37 (2), pp. 67–75, 2000.

[Aal11a] van der Aalst, W.M.P.: *Process mining: discovery, conformance and enhancement of business processes*. Springer, Berlin, 2011.

[Aal11b] van der Aalst, W.M.P.: *Intra- and Inter-Organizational Process Mining: Discovering Processes within and between Organizations*. 4th IFIP WG 8.1 Working Conference on the Practice of Enterprise Modeling, Lecture Notes in Business Information Processing, Vol. 92, pp. 1–11, 2011.

[Aal16] van der Aalst, W.M.P.: *Process Mining: Data Science in Action*. Springer, Berlin, Heidelberg, 2016.

[AAA12] van der Aalst, W.M.P.; Adriansyah, A.; Alves de Medeiros, A.K.; Arcieri, F.; Baier, T.; Blickle, T.; Bose, J.C.; van den Brand, P.; Brandtjen, R.; Buijs, J.; Burattin, A.; Carmona, J.; Castellanos, M.; Claes, J.; Cook, J.; Costantini, N.; Curbera, F.; Damiani, E.; de Leoni, M.; Delias, P.; van Dongen, B.F.; Dumas, M.; Dustdar, S.; Fahland, D.; Ferreira, D.R.; Gaaloul, W.; van Geffen, F.; Goel, S.; Günther, C.; Guzzo, A.; Harmon, P.; ter Hofstede, A.; Hoogland, J.; Ingvaldsen, J.E.; Kato, K.; Kuhn, R.; Kumar, A.; La Rosa, M.; Maggi, F.; Malerba, D.; Mans, R.S.; Manuel, A.; McCreesh, M.; Mello, P.; Mendling, J.; Montali, M.; Motahari-Nezhad, H.R.; zur Muehlen, M.; Munoz-Gama, J.; Pontieri, L.; Ribeiro, J.; Rozinat, A.; Pérez, H.S.; Pérez, R.S.; Sepúlveda, M.; Sinur, J.; Soffer, P.; Song, M.; Sperduti, A.; Stilo, G.; Stoel, C.; Swenson, K.; Talamo, M.; Tan, W.; Turner, C.; Vanthienen, J.; Varvaressos, G.; Verbeek, E.; Verdonk, M.; Vigo, R.; Wang, J.; Weber, B.; Weidlich, M.; Weijters, T.; Wen, L.; Westergaard, M.; Wynn, M.: *Process Mining Manifesto*. 9th International Conference on Business Process Management, Business Process Management Workshops, Vol. 99, pp. 169–194, 2012.

[ARW07] van der Aalst, W.M.P.; Reijers, H.A.; Weijters, A.J.M.M.; van Dongen, B.F.; Alves de Medeiros, A.K.; Song, M.; Verbeek, H.M.W.: *Business process mining: An industrial application*. Information Systems, Vol. 32 (5), pp. 713–732, 2007.

[AaW04] van der Aalst, W.M.P.; Weijters, T.: *Process mining: a research agenda*. Computers in Industry, Vol. 53 (3), pp. 231–244, 2004.

[AWM04] van der Aalst, W.M.P.; Weijters, T.; Maruster, L.: *Workflow mining: discovering process models from event logs*. IEEE Transactions on Knowledge and Data Engineering, Vol. 16 (9), pp. 1128–1142, 2004.

[Abb20] Abbyy, *State of Process Mining and Robotic Process Automation*. Online Source: https://www.abbyy.com/solutions/process-intelligence/research-report-2020/?success=true (Accessed on 01.07.2020), 2020.

[AQS01] Alon, I.; Qi, M.; Sadowski, R.J.: *Forecasting aggregate retail sales: a comparison of artificial neural networks and traditional methods*. Journal of Retailing and Consumer Services, Vol. 8 (3), pp. 147–156, 2001.

[ALG17] Aouachria, M.; Leshob, A.; Ghomari, A.: *Process Adaptation Patterns for Cross-Organizational Business Process Modeling*. 14th International Joint Conference on e-Business and Telecommunications (ICETE), Vol. 2, pp. 124–129, 2017.

[AsM20] Asmussen, C.B.; Møller, C.: *Enabling supply chain analytics for enterprise information systems: a topic modelling literature review and future research agenda*. Enterprise Information Systems, Vol. 14 (5), pp. 563–610, 2020.

[AzC13] Azzini, A.; Ceravolo, P.: *Consistent Process Mining Over Big Data Triple Stores*. IEEE International Congress on Big Data, pp. 54–61, 2013.

[BaS03] Barad, M.; Sapir, D.E.: *Flexibility in logistic systems – modeling and performance evaluation*. International Journal of Production Economics, Vol. 85 (2), pp. 155–170, 2003.

[BVL18] Barbosa, M.W.; Vicente, A.C.; Ladeira, M.B.; Oliveira, M.P.V.: *Managing supply chain resources with Big Data Analytics: a systematic review*. International Journal of Logistics Research and Applications, Vol. 21 (3), pp. 177–200, 2018.

[BeI17] Becker, T.; Intoyoad, W.: *Context Aware Process Mining in Logistics*. Procedia CIRP, Vol. 63, pp. 557–562, 2017

[Ber08] Bernabucci, R.J.: *Supply chain gains from integration*. Financial Executive, Vol. 24 (3), 2008.

[BCM14] Bernardi, M.L.; Cimitile, M.; Maggi, F.M.: *Discovering Cross-Organizational Business Rules from the Cloud*. IEEE Symposium on Computational Intelligence and Data Mining (CIDM), pp. 389–396, 2014.

[BCM18] Bernardi, M.L.; Cimitile, M.; Mercaldo, F.: *Cross-organisational process mining in cloud environments*. Journal of Information and Knowledge Management, Vol. 17 (2), 2018.

[BKM19] Bemthuis, R. H.; Koot, M.; Mes, M. R. K.; Bukhsh, F. A.; Iacob, M; Meratnia, N.: *An Agent-Based Process Mining Architecture for Emergent Behavior Analysis*. IEEE 23rd International Enterprise Distributed Object Computing Workshop (EDOCW), pp. 54–64, 2019.

[BoA11] Bouchbout, K.; Alimazighi, Z.: *Inter-Organizational Business Processes-Modelling Framework*. CEUR Workshop Proceedings, Vol. 789, pp. 45–54, 2011.

[BuM16] Buede, D.M.; Miller, W.D.: *The Engineering Design of Systems: Models and Methods*. Wiley Series in Systems Engineering and Management, Wiley, 2016.

[BDA12] Buijs, J.C.A.M.; van Dongen, B.F.; van der Aalst, W.M.P.: *Towards Cross-Organizational Process Mining in Collections of Process Models and their Executions*. 9th International Conference on Business Process Management, Lecture Notes in Business Information Processing, Vol. 100 (2), pp. 2–13, 2012.

[Cap16] Capgemini: *The Big Data Payoff: Turning Big Data into Business Value*. Online Source: https://www.capgemini.com/de-de/wp-content/uploads/sites/5/2017/07/the_big_data_payoff_turning_big_data_into_business_value.pdf (Accessed 29.06.2020), 2016.

[CMJ07] Che, H.; Mevius, M.; Ju, Y.; Stucky, W.; Trunko, R.: *A Method for Inter-organizational Business Process Management*. Proceedings of the IEEE International Conference on Automation and Logistics, 2007.

[CKL02] Chiu, D.K.W.; Karlapalem, K.; Li, Q.; Kafeza, E.: *Workflow View Based E-Contracts in a Cross-Organizational E-Services Environment*. Distributed and Parallel Databases, Vol. 12 (2–3), pp. 193–216, 2002.

[ClP14] Claes, J.; Poels, G.: *Merging Event Logs for Process Mining: A Rule Based Merging Method and Rule Suggestion Algorithm*. Expert Systems with Applications, Vol. 41 (16), pp. 7291–7306, 2014.

[CVW13] Comuzzi, M.; Vanderfeesten, I.; Wang, T.: *Optimized Cross-Organizational Business Process Monitoring: Design and Enactment*. Information Sciences, Vol. 244, pp. 107–118, 2013.

[DaH07] Davenport, T. H.; Harris, J. G.: *Competing on Analytics: The New Science of Winning*. Harvard Business School Press, Boston, Mass, 2007.

[DoA05] van Dongen, B.F.; van der Aalst, W.M.P.: *A meta model for process mining data*. Proceedings of the CAiSE Workshops, Vol. 2, pp. 309–320, 2005.

[EgH20] Eggers, J.; Hein, A.: *Turning Big Data into Value: A Literature Review on Business Value Realization from Process Mining*. Twenty-Eighth European Conference on Information Systems, 2020.

[EAZ12] Engel, R.; van der Aalst, W.M.P.; Zapletal, M.; Pichler, C.; Werthner, H.: *Mining Inter-organizational Business Process Models from EDI Messages: A Case Study from the Automotive Sector*.

4th International Conference on Advanced Information Systems Engineering, Vol. 7328, pp. 222–237, 2012.

[EKZ16] Engel, R.; Krathu, W.; Zapletal, M.; Pichler, C.; Bose, R.P.J.C.; van der Aalst, W.M.P.; Werthner, H.; Huemer, C.: *Analyzing inter-organizational business processes – Process mining and business performance analysis using electronic data interchange messages*. Information Systems and e-Business Management, Vol 14, pp. 577–612, 2016.

[FMW05] Fleischmann B.; Meyr H.; Wagner M.: *Advanced Planning*. Supply Chain Management and Advanced Planning, pp. 81–106, 2005.

[GCM09] Gerke, K.; Claus, A.; Mendling, J.: *Process Mining of RFID-based Supply Chains*. IEE Conference on Commerce and Enterprise Computing, 2009.

[Gor19] Górtowski, S.: *Supply Chain Modelling Using Data Science*. Business Information Systems Workshops, Springer International Publishing, pp. 634–645, 2019.

[HaS19] Halaška, M.; Šperka, R.: *Performance of an automated process model discovery – the logistics process of a manufacturing company*. Engineering Management in Production and Services, Vol. 11 (2), 2019.

[HKM19] Höpner, A.; Kapalschinski, C.; Müller, A.: *Deutsches Start-up Celonis erreicht Bewertung von 2,5 Milliarden Dollar*. Online Source: https://www.handelsblatt.com/technik/it-internet/process-mining-spezialist-deutsches-start-up-celonis-erreicht-bewertung-von-2-5-milliarden-dollar/25253078.html?ticket=ST-4129410-pfFGXlgackjVaFhRwVez-ap3 (Accessed on 15.06.2020), 2019.

[InG08] Ingvaldsen J.E.; Gulla J.A.: *Preprocessing Support for Large Scale Process Mining of SAP Transactions*. Business Process Management Workshops, Lecture Notes in Computer Science, Vol. 4928, 2008.

[ISV15] Irshad, H.; Shafiq, B.; Vaidya, J.; Bashir, M.A.; Shamail, S.; Adam, N.: *Preserving Privacy in Collaborative Business Process Composition*. 12th International Joint Conference on e-Business and Telecommunications, pp. 112–123, 2015.

[JBD08] Jain, V.; Benyoucef, L.; Deshmukh, S.G.: *A new approach for evaluating agility in supply chains using Fuzzy Association Rules Mining*. Engineering Applications of Artificial Intelligence, Vol. 21 (3), pp. 367–385, 2008.

[Joh14] Johnson, G.: *Trends in ERP software*. Quality, Vol. 53 (3), pp. 30–33, 2014.

[JoH16] Jonsson, P.; Holmström, J.: *Future of supply chain planning: closing the gaps between practice and promise*. International Journal of Physical Distribution & Logistics Management, Vol. 46 (1), pp. 62–81, 2016.

[JCS18] Jokonowo, B.; Claes, J.; Sarno, R.; Rochimah, S.: *Process Mining in Supply Chains: A Systematic Literature Review*. International Journal of Electrical and Computer Engineering (IJECE), 2018.

[JSR19] Jokonowo, B.; Sarno, R.; Rochimah, S.; Priambodo, B.: *Process mining: measuring key performance indicator container dwell time*. Indonesian Journal of Electrical Engineering and Computer Science, Vol. 16 (1), 2019.

[KuH02] Kuhn, A.; Hellingrath, B.: *Supply Chain Management: optimierte Zusammenarbeit in der Wertschöpfungskette*. Engineering online library, Springer, Berlin, 2002.

[KaS17] Kache, F.; Seuring, S.: *Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management*. International Journal of Operations & Production Management, Vol. 37 (1), pp. 10–36, 2017.

[KLK09] Khan, A.; Lodhi, A.; Köppen, V.; Kassem, G.; Saake, G.: *Applying Process Mining in SOA Environments*. 7th International Conference on Service Oriented Computing, Vol. 6275, pp. 293–302, 2009.

[KOJ20] Kim, A.; Obregon, J.; Jung, J.-Y.: *PRANAS: A Process Analytics System*

Based on Process Warehouse and Cube for Supply Chain Management. Applied Sciences, Vol. 10, 2020.

[KPT19] Klinkmüller, C.; Ponomarev, A.; Tran, A.B.; Weber, I.; van der Aalst, W.M.P.: *Mining Blockchain Processes: Extracting Process Mining Data from Blockchain Applications*. Blockchain and Central and Eastern Europe Forum, Springer International Publishing, 2019.

[KGG11] Koh, S.C.L.; Gunasekaran, A.; Goodman, T.: *Drivers, barriers and critical success factors for ERPII implementation in supply chains: A critical analysis*. The Journal of Strategic Information Systems, Vol. 20 (4), 2011.

[LHZ09] Lau, H.C.W.; Ho, G.T.S.; Zhao, Y.; Chung, N.S.H.: *Development of a process mining system for supporting knowledge discovery in a supply chain network*. International Journal of Production Economics, Vol. 122, pp. 176–187, 2009.

[LeW07] Legner, C.; Wende, K.: *The Challenges of Inter-organizational Business Process Design - a Research Agenda*. 15th European Conference on Information Systems, 2007

[Li10] Li, Y.: *An Automatic Virtual Organization Structure Modeling Method in Supply Chain Management*. International Conference on Management and Service Science, 2010.

[LDZ16] Liu, C.; Duan, H.; Zeng, Q.T.; Zhou, M.C.: *Towards Comprehensive Support for Privacy Preservation Cross-Organization Business Process Mining*. IEEE Transactions on Service Computing, Vol. 12 (4), pp. 639–653, 2016.

[LMF16] Lu, Y.; Morris, K.C.; Frechette, S.: *Current standards Landscape for smart manufacturing systems*. National Institute of Standards and Technology, 2016.

[Mag20] Magenheim-Hörmann, T.: *Das Einhorn aus München.* Online Source: https://www.fr.de/wirtschaft/einhorn-muenchen-13419862.html (Accessed on 15.06.2020), 2020.

[MWW03] Maruster, L.; Wortmann, J.C.; Weijters, T.; van der Aalst, W.M.P.: *Discovery distributed processes in supply chains*. Collaborative Systems for Production Management, IFIP — The International Federation for Information Processing, Vol. 129, pp. 219–230, Springer, 2003.

[Mol05] Møller, C.: *ERP II: a conceptual framework for next-generation enterprise systems?* Journal of Enterprise Information Management, Vol. 18 (4), pp. 483–497, 2005.

[PaK05] Park, K.; Kusiak, A.: *Enterprise resource planning (ERP) operations support system for maintaining process integration*. International Journal of Production Research, Vol. 43 (19), pp. 3959–3982, 2005.

[PKB17] Pourmasoumi, A.; Kahani, M.; Bagheri, E.: *Mining variable fragments from process event logs*. Information Systems Frontier, Vol. 19, pp. 1423–1443, 2017.

[RoC19] Rojas E.; Capurro D.: *Characterization of Drug Use Patterns Using Process Mining and Temporal Abstraction Digital Phenotyping*. International Conference on Business Process Management, Vol. 342, 2019.

[RoH20] Roth, S.L.; Heimann, T.: *Digitalisierung und intelligente Technologien*. Capgemini Studie IT-Trends 2020. Online Source: https://www.capgemini.com/de-de/wp-content/uploads/sites/5/2020/02/IT-Trends-Studie-2020.pdf (Accessed on 01.07.2020), 2020.

[RLM12] Rozsnyai, S.; Lakshmanan, G.T.; Muthusamy, V.; Khalaf, R.; Duftler, M.J.: *Business Process Insight: An Approach and Platform for the Discovery and Analysis of End-to-End Business Processes*. Annual SRII Global Conference, pp. 80–89, 2012.

[San16] Sanders, N.R.: *How to Use Big Data to Drive Your Supply Chain*. California Management Review, Vol. 58 (3), pp. 26–48, 2016.

[SZW11] Sun, S.X.; Zeng, Q.; Wang, H.: *Process-Mining-Based Workflow Model Fragmentation for Distributed Execution*. IEEE Transactions on Systems, Man, and Cybernetics, Vol. 41 (2), 2011.

[TCC17] Tao, F.; Cheng, J.; Cheng, Y.; Gu, S.; Zheng, T.; Yang, H.: *SDMSim: A manufacturing service supply–demand matching simulator under cloud environment*. Robotics and Computer-Integrated Manufacturing, Vol. 45, pp. 34–46, 2017.

[TYB02] Tarn, J.M.; Yen, D.C.; Beaumont, M.: *Exploring the rationales for ERP and SCM integration*. Industrial Management & Data Systems, Vol. 102 (1), pp. 26–34, 2002.

[TFB18] Thiede, M.; Fuerstenau, D.; Barquet, B.A.P.: *How is process mining technology used by organizations? A systematic literature review of empirical studies*. Business Process Management Journal, Vol. 24 (4), pp. 900–922, 2018.

[TöT19] Tönnissen, S.; Teuteberg, F.: *Using Blockchain Technology for Cross-Organizational Process Mining - Concept and Case Study*. Business Information Systems, Springer International Publishing, pp. 121–131, 2019.

[WHT18a] Wang, Y.; Hulstijn, J.; Tan, Y.: *Regulatory supervision with computational audit in international supply chains*. Proceedings of the 19th Annual International Conference on Digital Government Research: Governance in the Data Age, pp. 1–10, 2018.

[WHT18b] Wang, Y.; Hulstijn, J.; Tan, Y.: *Towards Smart Manufacturing: Compliance Monitoring for Computational Auditing*. Research Papers, Vol. 93, 2018.

[YSB16] Yahya, B.N.; Song, M.; Bae, H.; Sul, S.O.; Wu, J.Z.: *Domain-driven actionable process model discovery*. Computers and Industrial Engineering, Vol. 99, pp. 382–400, 2016.

[ZSD13] Zeng, Q.; Sun, S.X.; Duan, H.; Liu, C.; Wang, H.: *Cross-organizational collaborative workflow mining from a multi-source log*. Decision Support Systems, Vol. 54 (3), pp. 1280–1301, 2013.

Christoph Jacobi, M.Sc. is research associate at the Institute for Material Handling and Logistics (IFL) at the Karlsruhe Institute of Technology (KIT). His research focuses on performance evaluation of production and supply chain networks using discrete-time queueing theory.

Karlsruhe Institute of Technology (KIT)
Institute for Material Handling and Logistics (IFL)
Gotthard-Franz-Str. 8, 76131 Karlsruhe
Fon: +49 721 608 48626
E-Mail: jacobi@kit.edu

Mathias Meier, M.Sc., studied Industrial Engineering and Management at the Karlsruhe Institute of Technology (KIT) and works as Senior Consultant at Barkawi Management Consultants GmbH & Co. KG.

Barkawi Management Consultants GmbH & Co. KG
Baierbrunner Str. 35, 81379 Munich
E-Mail: mathias.meier@genpact.barkawi.com

Lutz Herborn, M.Sc., is student at the Karlsruhe Institute of Technology (KIT). In his master thesis, Lutz Herborn studied the application of process mining in supply chains.

Karlsruhe Institute of Technology (KIT)
Institute for Material Handling and Logistics (IFL)
Gotthard-Franz-Str. 8, 76131 Karlsruhe
Supervised by Christoph Jacobi
E-Mail: lutz.herborn@student.kit.edu

Prof. Dr.-Ing. Kai Furmans is the director of the Institute for Material Handling and Logistics (IFL) at the Karlsruhe Institute of Technology (KIT).

Karlsruhe Institute of Technology (KIT)
Institute for Material Handling and Logistics (IFL)
Gotthard-Franz-Str. 8, 76131 Karlsruhe
Fon: +49 721 608 48600, Fax: +49 721 608 48629
E-Mail: furmans@kit.edu