SUPPLY CHAIN RESILIENCE MANAGEMENT USING PROCESS MINING

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ABSTRACT

Recent events such as the Coronavirus Pandemic or the disruption of the Suez Canal have shown how vulnerable supply chains can be and have led to an increased focus on resilience analysis by companies. We believe that all the data needed to understand the resilience status of a supply chain and identify opportunities for improvement already exist within companies. Therefore, we provide an approach to guide decision makers in this regard. We propose to first perform a rough resilience analysis using a limited set of transactional data. This analysis is based on key resilience areas to identify vulnerable elements of the supply chain that should be further investigated in terms of specific entities, transport relations, and materials. Based on these elements, process mining becomes a promising approach to understand the underlying actions, problems, and possible bottlenecks and to reveal improvement strategies.

INTRODUCTION

The goal of this article is to focus on systematic, performance-based risk and resilience management for supply chains. Therefore, our research deals with the questions of (1) how to provide an easy-to-use process for decision makers to identify the relevant data required to monitor the resilience status from a strategic perspective, and (2) how to understand the processes and implications of their supply chain risk management efforts.

Accordingly, performance measurement should explicitly be used in the sense of resilience. Therefore, critical disruptive factors and problem sources for relevant supply chain processes are to be identified and prioritized. Both (inter-)dependencies and the relevance of risks are to be evaluated and summarized into profiles. Related analyses enable proactive decisions and actions. Optimizing processes in terms of resilience implies using new knowledge and capabilities and applying different process-oriented performance measurements. This article examines the extent to which process mining is suitable for ensuring associated supply chain risk management.

The remainder of this paper is organized as follows: in the next section, the concept of process mining is discussed from a general perspective. We subsequently highlight how to analyze the triggers of supply chain disruptions on the basis of transaction data. The resulting vulnerabilities in the supply chain are the starting point for a detailed analysis in terms of process mining. Finally, a conclusion is drawn, and the tasks of future research are outlined.

GENERAL CONSIDERATIONS

Supply chains can be viewed as complex systems in which different business processes exist within and across companies and whose efficiency depends on how well they are interlinked or coordinated. The process mining approach offers an option to analyze and optimize supply chain processes. The question of whether the associated use of this technology proves meaningful is the starting point for the following considerations.

Process mining is an interface technology that links data mining methods with the use of process management (van der Aalst et al. 2012; Ramesh et al. 2020). Key figures can be used to identify relevant or critical business processes and the associated process optimization potential.

The state-of-the art literature differentiates three process mining approaches: discovery, conformance checking, and enhancement. In the course of discovery, information is read unchanged from an event log and displayed. This allows companies to gain transparency about the actual processes. During the conformance check, the expected process flow is compared with the actual process flow. For this purpose, a process mining tool analyzes the correspondences or deviations between an existing target process model and the variants in the actual. Process mining enhancement aims to extend or optimize the existing process structure.

Information about the as-is process flow is extracted from the event log and added to the existing process model. In comparison to the conformance check, the extension is not limited to the comparison between actual and target process but integrates the identified deviations directly into the process model (van der Aalst et al. 2012). In addition to the aforementioned approaches, a further manifestation of process mining can be identified in practice: it involves the operational support of IT-based systems. Here, insights gained from process mining applications are used to support the process execution of operational systems in real time. For example, decisions

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can be made based on empirical values from past process execution (Peters and Nauroth 2019). The permanent maintenance of the event log enables real-time analysis.
The evaluation criteria described below can serve as a basis for decisions and provide statements on whether process mining is applicable to supply chain processes. For the identification of the central building blocks in the sense of a framework, three different perspectives are taken: the first perspective includes requirements that are relevant for the goal setting process of the involved companies with regard to process mining. From the second perspective, the analysis of the supply chain process structure is performed. The third perspective deals with the data basis of the supply chain processes under consideration.
Before using process mining, suitable goals or questions should be defined. In this case, it is a matter of identifying vulnerable process areas of a supply chain with the help of resilience performance checks and taking optimization measures on the basis of the analyzed weak points. In addition to generating actual process models, it is also possible to compare this with an existing target process model (e.g., within the Supply Chain Operations Reference (SCOR) framework) or to extend the existing process model (van der Aalst et al. 2012). In addition, process mining can be used for real-time-based decision making (Peters and Nauroth 2019).
In order to specify how to use process mining in the company, it should be stated in the goal setting which process mining approaches are relevant for the company. An existing process model has to be available both for the process mining conformance test and for the process mining extension.
Process mining focuses on process analysis. However, not all business processes have the same value for the supply chain. Rather, they can be distinguished and differentiated from one another on the basis of different characteristics in terms of resilience in the sense of a preselection. Therefore, an approach is required that ensures that relevant elements of the supply chain are identified to be further processed via process mining.
A process characteristic which has a direct impact on the application of process mining methods, for example, is the degree of structuring of a process. This determines how precisely and in detail a business process has been defined and how often it deviates from its process flow chart (Allweyer 2005). However, if so-called concept shifts are incorrectly identified as process deviations, this leads to an erroneous interpretation of the process mining model. Identified concept shifts must therefore be taken into account when considering the model (Hierzer 2017). In this case, it is a matter of changing from an efficiency orientation to a resilience orientation, or rather an adequate balance.
Furthermore, it proves useful to examine the process-related capabilities of the parties involved. Process mining benefits from a solid, digitally oriented process and data infrastructure (van der Aalst et al. 2012). In the present case, it is assumed that this already exists in supply chain management. Otherwise, corresponding capabilities should be built up first.
Maturity models can be used to evaluate the suitability of a business process for process mining (Becker et al. 2009). To determine the process maturity level, a suitable process maturity model has to be identified and this must be transferred into an evaluation framework. The evaluation should be carried out on the basis of uniformly formulated criteria, for example on the basis of a decision matrix. This is typically an extension of the Capability Maturity Model Integration (CMMI). For this purpose, business processes are classified into defined levels on the basis of specific process objectives and characteristics (Bürgin 2007). The process objectives and process characteristics of the individual maturity levels can be a benchmark for the process maturity level.
Another prerequisite for the efficient use of process mining is to have consistent access to all essential information. In this case, the relevant data must first be identified, merged, and structured in a uniform granularity (Hierzer 2017). Thus, the structure of the event data must be reviewed if the process is handled by several systems, which can be assumed in the context of supply chain management. Criteria such as the recording frequency of the process data, the respective data granularity as well as the process reference of the data should be used for the analysis. If an associated uniform structure is missing, this must be created. Otherwise, the use of a process mining tool proves inadequate.
Data from application systems can be interpreted as "raw material" for a process mining tool. To generate a process model that reflects reality as accurately as possible, the data basis must be of the highest possible quality. Accordingly, the data to be used later as event data must be analyzed in advance – which is in particular true when dealing with complex supply chain networks. A suitable evaluation method for this purpose is the maturity model developed by Wil van der Aalst: similar to the principle of process maturity models, the event log maturity model classifies the event logs under consideration into different levels based on certain criteria and characteristics (van der Aalst et al. 2012). To generate a robust process model, the event log under consideration should have a maturity level of at least three (Peters and Nauroth 2019; van der Aalst et al. 2012).
Only if a suitable data basis is available, it proves useful to analyze the attributes of the event logs. As a general rule, the more attributes there are in the event log, the more details can be represented in the process model. The analysis of the attributes is necessary to check whether the event log contains all relevant data for the goal fulfillment. If, for example, the objective requires that incidents be evaluated for each customer, it is necessary to check whether the data basis of the event log permits an assignment between customer and incident.

SUPPLY CHAIN RESILIENCE ANALYSIS

Recent events such as the coronavirus pandemic or the disruption of the Suez Canal have shown how fragile supply chains can be. These events have meant that reliable supplies of ordered goods to customers at various stages of the value chains could no longer be guaranteed. As in other socially relevant areas, there has been an increased discussion about the *resilience* of supply chains. This discussion is directly related to the availability and application of suitable supply chain risk management approaches in companies.

Fundamentally, supply chain risk management has been on the corporate agenda for many years. As part of their efforts, companies can turn to one of the many commercial IT tools that typically suggest and promise assistance in developing reactive emergency response. They enable operational business continuity by providing tailored decision-relevant information that can be used to initiate ad hoc measures such as changing the transportation mode from sea freight to emergency air to deal with a port strike.

We confirm that the use of such tools is indeed very valuable to manage supply chain risk on a daily basis as they deal with high probability low impact events. Therefore, we highlight the vendors' claim that their tools increase operational resilience in the supply chain. However, the limitations of these tools become apparent when it comes to the overall functionality of supply chains during an incident, as it was the case with the recent events mentioned above.

Events such as the current pandemic are characterized by low probability and (potentially) severe impact. Therefore, the focus of our research is on ways to monitor the overall functioning of the networks during disruptive events and thus understand supply chain resilience from a strategic perspective. This is of great importance because only if this holistic resilience status is transparent, in-depth analysis are useful to identify proactive decision options that can be made in advance to safeguard against disruptive events, e.g., adjustments to the current supply chain design.

From a theoretical point of view, the resilience of a supply chain can be defined by its ability to recover from a disruptive event and even reach a higher level of performance in the long run (Anbumozhi et al. 2020). Several authors have provided a classification of concrete actions that can be selected by decision makers to improve the resilience of their networks. For example, Melnyk et al. (2014) present a set of "investments" to improve resilience, such as investments in discovery, information, operational flexibility, and buffers. Although these investments are useful to achieve improvements, they are valuable only if decision makers are informed about the true state of resilience of their networks. We believe that it is precisely this transparency that is extremely important as an upstream step, as it allows decision makers not to make decisions "in the dark" but to know exactly where and what vulnerabilities exist in their supply chains.

Therefore, our research focuses on the questions of (1) how to provide an easy-to-use process for decision makers to monitor resilience status from a strategic perspective, and, which subsequently applies resilience-related data to (2) understand, evaluate, and improve the processes regarding their supply chain risk management efforts.

We believe that these goals can be achieved if companies perform resilience analysis that is clearly based on data. A supply chain is always characterized by the physical flows that take place between different entities. These can be factories and warehouses (intra supply chain) or suppliers and customers (b2b and b2c) (inter supply chain). The physical flows can occur in any relationship between these entities and each flow is therefore defined as a material-specific delivery between a sender and a receiver location. The core idea of our research regarding (1) is to define a limited set of data which is sufficient to get a first idea regarding the status of strategic resilience. Based on the result, elements of the supply chain (e.g., specific materials, entities, relations) can be revealed whose disruptions would lead to major turbulence in the supply chain and, thus, would have a negative effect on the supply chain’s overall resilience.

Regarding the first research objective, this means that our proposal is to avoid elaborated and detailed models of the supply chain with sophisticated analyses, but to first perform a rough analysis of the weaknesses and strengths of the network to get a first indication of the strategic resilience status. Therefore, a data-based supply chain model is to be developed on the basis of a limited amount of transaction data that a company has anyway (Schätter and Morelli 2021). In order to translate this data into insights about the strategic resilience status of the company, a limited number of transaction data can be considered sufficient, as highlighted in Table 1.

Table 1: Data sets for supply chain resilience analysis

Data set	Description
Sender ID	Source of physical flow
Sender City	City in which sender is located
Receiver ID	Sink of physical flow
Receiver City	City in which receiver is located
Material ID	Unique ID of delivered material
Sending date and time	Date at which delivery has started
Receiving date and time	Date at which delivery has finished
Distance of delivery	Distance between sending and receiving location
Duration of delivery	Duration between sending and receiving location
Volume of delivery	Volume of the delivery [m3]

The limited transaction data highlighted in Table 1 can be easily captured from corporate data warehouses, ERP systems or SCM systems. Nevertheless, the data contains all the information needed to strategically analyze the effects of potential disruptions and vulnerabilities within the supply chain. Thus, we offer a cost-efficient method for an initial resilience analysis. Based on the data, we aim at uncovering vulnerabilities within the supply chain that could affect smooth functioning during a disruptive event. They thus provide information on the state of resilience which are in the following understood as *key resilience areas (KRA)*:

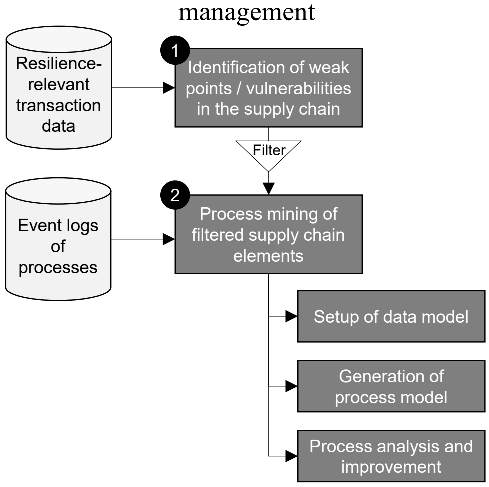
- *KRA1 - geographic distribution of entities:* visibility into the locations and distribution of entities (factories, warehouses, suppliers, customers) provide an initial indication of supply chain resilience. For example, large aggregations of suppliers in certain areas increase the risk of large-scale disruptions within the network if a risk event affects the entire area. The geographic distribution (e.g., the number of customers per city) can be captured directly from the geographic datasets (sender and receiver cities).
- *KRA2 - sourcing strategy of materials:* using a single-sourcing approach for certain materials provides cost benefits but is one of the most important aspects of managing the impact of supply disruptions. There are no redundancies for these materials, so a supplier failure can lead to a shortage of the material (unless other inventory is available). Through data analysis, it is possible to directly determine what proportion of materials is not purchased on the basis of a multi-sourcing strategy. by analyzing which material IDs are supplied by only one sender ID.
- *KRA3 - warehouse materials:* one of the most positive impacts on supply chain resilience can be buffer stocks of certain materials in warehouses. This allows temporary outages of certain suppliers to be bridged without negatively impacting supply chain performance. The dataset allows for an analysis of material IDs and quantities delivered to warehouses during the period under consideration. We believe that this information is sufficient for a rough first check. Of course, further data can be optionally included to the data such as “inventory snapshots”, indicating inventories per material and month.
- *KRA4 - average storage time:* a further indication of the resilience of the network in terms of buffers, linked to point 3, refers to the average time materials are stored in the warehouse. The data described show all physical upstream flows into the warehouses as well as all physical downstream flows to the next entity. Based on this data, the average time can be estimated as the total quantity of a stocked material in relation to demand. This allows critical materials to be identified.
- *KRA 5 - transport delays:* for each relation, the distance and average delivery duration is available. By comparing these target data with the actual delivery durations, which can be derived by comparing the sending and receiving times, delays in the supply chain become visible. In this way, critical transport relations can be identified and both sending or receiving entities in the supply chain, delay-prone material IDs, and the corresponding delivery volumes [m3] can be analyzed.
- *KRA6 - consolidation of deliveries:* based on the data, consolidation of material deliveries between shipping and receiving locations can be estimated. Deliveries should generally be consolidated, e.g., different materials delivered in the same relation on the same day should be combined. This leads to better utilization of shipments with positive cost effects. In addition, consolidation can have a positive impact on resilience, as the relation is used by fewer individual deliveries, which reduces the risk of disruptions (e.g., due to congestion). Consolidation can be read directly from the data by counting the delivery days and delivery quantities per relation.
- *KRA7 - transport distance:* the data allows an analysis of the transport distances between the used transport relations. Thus, the share of regional deliveries in inbound and/or outbound transports compared to long-distance transports can be determined. Furthermore, the data for each transport distance can be used to read off the actual volumes delivered in the reference period. In principle, more national and regional networks reduce the risk of large-scale, global disruptions.
- *KRA8 - intra-logistics processes:* the data enables transparency regarding the processes from an intra-logistical perspective. Thus, it can be analyzed which materials are delivered to which warehouses and in which factories they are further processed. From a resilience perspective, for example, it is possible to assess which elements of the company's own supply chain are particularly dependent on critical materials and can therefore be affected by disruptions. Insights regarding the intra-logistics processes might be already included in the further KRAs. However, we suggest considering those processes as explicit category because weaknesses within the internal supply chain can be revealed.

Hence, rather than focusing on overly analytical approaches to assess the status quo of resilience, our research focuses on ways to assist logistics managers in an easily applicable and pragmatic manner. We believe that the data highlighted above, and the guidance provided in the eight KRAs of analysis, are sufficient to provide an initial understanding of the status of the supply chain from a strategic perspective. To extend and enhance this analysis in terms of monitoring the actions taken by decision makers leading to the physical flows shown by the data, we believe *process mining* is a promising approach. Therefore, the next chapter focuses on the basic considerations for using process mining in supply chain resilience management.

SUPPLY CHAIN RESILIENCE MANAGEMENT BASED ON PROCESS MINING

Regarding our research objective (2), we aim at improving supply chain resilience by analyzing critical elements of the supply chain and underlying processes and actions in order to identify concrete improvement opportunities. The basic principle of our approach is shown in Figure 1. The starting point refers to the data set and the analysis of the KRAs to identify vulnerabilities and susceptibilities within the supply chain (Step 1). We assume that to gain deeper insight into these vulnerabilities, it is promising to analyze the processes behind the vulnerabilities in more detail. At this point, we propose to focus on process mining (Step 2). In fact, the identified vulnerable supply chain elements are used as filters to cut the focus area of the supply chain and the process areas to be considered, such as single-source suppliers, relationships prone to transportation delays, or relationships characterized by weak consolidation in the past. Finally, improvement opportunities should emerge from the process mining.

Figure 1: Approach of supply chain resilience management



Step 1: Identification of weak points / vulnerabilities in the supply chain

As mentioned earlier, the supply chain is defined by the physical flows in the form of material-specific deliveries that are included in the transaction data set. Step 1 can therefore be understood as a filter to identify the relevant elements of the supply chain on which the subsequent process mining should focus. Hence, the KRA analysis has to create transparency regarding vulnerable entities, transport relations, and specific materials:

- *Vulnerable entities* can be identified primarily by KRA1, KRA2, KRA6, and KRA8. The geographic distribution of entities (KRA1) highlights specific suppliers, customers, warehouses, and factories that are in an unusual environment, for example, because they are highly clustered or located in areas of political risk. KRA2 considers suppliers that are linked to a single sourcing strategy and are therefore vulnerable to disruption. KRA6 suggests generally considering shippers that are characterized by a high mix of materials delivered on different shipping days; this could indicate poor consolidation of supplies and, thus, increasing vulnerability to disruption. Finally, KRA8 should point to intralogistics operations such as factories and warehouses that may be vulnerable to critical materials due to high volumes, for example.
- *Vulnerable transport relations* can be identified primarily by KRA5 and KRA7. The dataset shows transport delays in physical flows (KRA5), which occur when there is a significant discrepancy between the expected duration of delivery and the difference between the timestamps of the send and receive dates and times. KRA7 is based on a static analysis of transport relations that may be at risk because they run over long distances. These relations can be selected directly from the data set.
- *Vulnerable materials* can be identified primarily by KRA3 and KRA4. First, the most important materials in terms of volume that are temporarily stored in warehouses should be considered in more detail. This can be done by looking at the high input volume flows into the warehouses (KRA3). In addition, those materials that are stored for only a limited or no time are also considered critical, as they are of great importance for maintaining the supply chain. In this context, an analysis of the time stamps between the input and output flows to and from the warehouses is required (KRA4).

All elements related to the above endangered entities, transport relations, and materials must be filtered. For example, by following the vulnerable transport relations, the corresponding entities and materials should be part of the further analyses. The filter reduces complexity as it highlights the supply chain's elements that are important for resilience management using process mining.

Step 2: Process mining of filtered supply chain elements

Data is needed as "raw material" for a process mining tool. Instead of trying to gain insights into resilience-relevant actions of decision makers by processing all available transaction data of deliveries for a specific reference point in time, our approach proposes to first perform a rough analysis of potentially critical elements in the supply chain in order to reduce complexity. This is in line with the assumptions of process mining, since the event data need to be analyzed in advance. We suggest that process mining for supply chain resilience management should follow a practical application of the general steps of discovery, conformance checking, and enhancement (see section "General Considerations"). From a practical perspective this means that first a data model should be built, second a process model should be generated based on process mining algorithms followed by the identification of optimization potential.

Set up of data model

Data extraction into an event log represents an integral part of process mining activities. The event log has to contain the relevant data for the relevant process under consideration. Then, based on the traces of the underlying

IT systems (i.e., database entries), process mining algorithms can reconstruct the as-is process flows by connecting events to activities.
An event log can be regarded as a particular view of the event data available. The assumption about event logs is that a process consists of cases, which comprise events, and the events within a case are ordered (van der Aalst 2018a). Therefore, three components for business processes are required: a date stamp, a characterization of the event (e.g., "goods receipt" activity), and a key ("case id") to this operation (e.g., "purchase order item"). Each case consists of a sequence of events carried out within a process instance. Each unique sequence of events from the beginning to the end of a process instance is referred to as a variant, and each case/trace belongs to exactly one (Suriadi et al. 2017).
Regarding resilience process analysis, it is necessary to store additional data elements (attributes) to use information about resources and the organizational perspective (entities, transport relations, and materials) for later discoveries and / or enhancements. As supply chain management comprises several business processes, multi-event logs have to be considered as an adequate data source. The critical elements of the supply chain identified in the previous analysis are now the subject of process mining. Thus, all actions related to these elements of the supply chain should be further processed. This might be, for example, all actions taken for transport scheduling or order processing. These are basically all steps in the purchase-to-pay process starting with demand planning, through supplier selection, disposition, approval and monitoring to goods receipt.
Taking the example of KRA2, we might have identified a material that has been exclusively ordered from only one supplier for the given time period. All actions taken by the planner leading to the resulting single-sourcing are part the event log and its capturing is therefore the first steep of process mining.
The quality of the data (both form and content) reveals to be critical for the overall success. On the one hand, the preparation of event logs for our strategic application case has to focus on the relevant data following Occam´s razor in the sense of simplicity and granularity. On the other hand, it has to minimize information loss so that the event log is valid in the context of the resilience domain. From a technical perspective, XES ("extensible event stream") can be used as a future data format standard, instead of the MXML format, as it is suitable for exchanging event logs between process mining and simulation tools (van der Aalst 2018b).

Generation of process model

Process mining algorithms create a process flow out of the traces from the event log. This is the basis for further discoveries, conformance checks, and /or enhancements. The algorithm used needs to generalize the behavior contained in the event log to show the most likely underlying model that is not invalidated by the next set of observations. Especially the balance between "overfitting" (creating a model too specific) and "underfitting" (generating a model too general) reveals as a challenge for this phase (van der Aalst 2018a).
Taking again the example of single-sourcing, process mining algorithms allow to plot all actions included in the event log. Thus, the standard process of ordering material becomes transparent. In addition also deviations from the standard are revealed such as buying from only one source although the standard specifies a split between two suppliers that goes along with a reduced risk.
The control flow perspective as well as the organizational perspective must be considered regarding the target group and its willingness for acceptance. The process model has to provide transparency, allowing to trace process flows, analyze delays, loops and to identify complexity drivers (Reinkemeyer 2020). Furthermore, resilience performance measures have to be extracted or calculated from the event log data.

Process analysis and improvement

The analysis takes place on the created process model and the provided performance measures to enable data-driven decision making and to discover as well as to monitor. For the supply chain management, the logistics orchestration becomes transparent. The KRAs form the basis for value proposition considerations regarding resilience, due to the holistic approach.
In the example of single sourcing, it might become obvious that although there is a second supplier established, only one supplier received the orders. This gives a clear indication for possible improvement in terms of activating the second available supplier.
Besides this, conformance checks for different process variants are possible to find communalities as well as discrepancies. Furthermore, process mining can be combined with business process management efforts to optimize the as-is model by creating a to-be model (e.g., based on the SCOR framework). This enhancement approach changes or extends the a-priori model. There is also a benchmarking opportunity, based on the key performing indicators created (e.g., costs, throughput time or rework).

CONCLUSION AND OUTLOOK

It seems that the aim of uncovering vulnerabilities in the supply chain by using transaction data and KRAs as a starting point can be advanced by a subsequent process mining: based on the existing IT infrastructure like data warehouses, ERP software and/or SCM systems, it is possible to compose data (and meta data) and convert them into an event log. The challenges are limited, as the required data is structured in contrast to the domain of social media. However, it has to be ensured that additional data (entities, transport relations, and the warehouse material flow) are adequately mapped.
The target of creating an end-to-end supply chain process promises to be manageable from a strategic point of view: it is the core focus of process mining to create as-is variants out of the event log. The challenge is to avoid "overfitting" and "underfitting". Discovery as a type of

process mining offers an adequate platform for analysis. It can be enhanced by other procedures like conformance checking, enhancement, and bench-marking.

As an outlook, event logs created for process mining reasons also can be used as a fundament for constructing predictive models (van der Aalst 2018a). However, to switch from backward-looking by the process mining approach to design alternatives and to anticipate the future simulation is a promising choice: corresponding work may employ different "what if" issues to be answered and alternatives with respect to the resilience indicators are able be evaluated. Various scenarios to combine process mining and simulation can be used therefore (van der Aalst 2018b).

We believe that the approach described in this contribution is promising to support decision makers in understanding their supply chains with respect to resilience – a requirement that has been significantly revealed by past supply chain disruptions. Our suggestions ensure that the relevant elements of the supply chain that provide insights regarding the resilience status are identified in a pragmatic and cost-efficient manner. In this regard, an important next step of our research will be to evaluate the proposed KRAs: are they sufficient to understand the network under consideration in terms of resilience? Are there overlaps in the KRAs or should additional categories be included? Therefore, a case study based on real corporate transaction data is currently underway.

The initial resilience analysis sets the basis to apply a process mining approach in order to understand the actions of the decision makers on the different management levels and to identify improvements. We have exemplarily highlighted how this would look like for a typical purchasing process. Future research should provide a prioritization of the specific disposition processes (e.g., order and transport scheduling) that should be analyzed in this regard. The concrete augmentation of the underlying specifications (e.g., event log) is work in progress as well as the verification and illustration of the approach with real company data and therefore an essential part of our future research.

REFERENCES

Allweyer, T. 2005. *Geschäftsprozessmanagement, Strategie, Entwurf, Implementierung, Controlling*. W3L-Verlag, Herdecke, Bochum.

Anbumozhi, V.; F. Kimura; S. Mugan Thangavelu. 2020. *Supply chain resilience, Reducing vulnerability to economic shocks, financial crises, and natural disasters*. Springer, Singapore.

Becker, J.; R. Knackstedt; J. Pöppelbuß. 2009. "Entwicklung von Reifegradmodellen für das IT-Management." *Wirtschaftsinformatik* 51, No.3, 249–260.

Bürgin, C. 2007. *Reifegradmodell zur Kontrolle des Innovationssystems von Unternehmen*. Doctoral Thesis, ETH Zurich.

Hierzer, R. 2017. *Prozessoptimierung 4.0, Den digitalen Wandel als Chance nutzen*. Haufe Gruppe, Freiburg, München, Stuttgart.

Melnyk, S.; D.J. Closs; S. Griffis; C. Zobel; J. Macdonald. 2014. "Understanding supply chain resilience." *Supply Chain Management Review* 18, 34–41.

Peters, R. and M. Nauroth. 2019. *Process-Mining, Geschäftsprozesse: smart, schnell und einfach*. Springer Fachmedien, Wiesbaden.

Ramesh, G.S.; T.V. Ranjini Kanth; D. Vasumathi. 2020. "A Comparative Study of Data Mining Tools and Techniques for Business Intelligence". In *Performance Management of Integrated Systems and its Applications in Software Engineering 2020*, M. Pant, T.K. Sharma, S. Basterrech, C. Banerjee (Eds.), Springer, Singapore, 163–173.

Reinkemeyer, L. 2020. *Process mining in action, Principles, use cases and outlook.* Springer, Cham.

Schätter, F. and F. Morelli. 2021. "Business Process Simulation Focusing Supply Chain Risk Management Aspects". In *Special Track: Simulation and Modelling in Supply Chains, along with SIMUL 2021*, 38–43.

Suriadi, S.; R. Andrews; A. ter Hofstede; M.T. Wynn. 2017. "Event log imperfection patterns for process mining: Towards a systematic approach to cleaning event logs." *Information Systems* 64, 132–150.

van der Aalst, W. 2018a. *Process Mining, Data Science in Action.* Springer, Berlin.

van der Aalst, W. 2018b. "Process Mining and Simulation: A Match Made in Heaven!" In *Proceedings of the 50th Computer Simulation Conference: Society for Modeling and Simulation International (SCS)*.

van der Aalst, W.; A. Adriansyah; A.K.A. de Medeiros; F. Arcieri; T. Baier; T. Blickle et al. 2012. "Process Mining Manifesto". *In Business Process Management Workshops. BPM 2011 International Workshops, Clermont-Ferrand, France, August 29, 2011*, F. Daniel, K. Barkaoui, S. Dustdar (Eds.). Springer, Berlin, 169–194.

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