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Digitalized value stream mapping: review and outlook

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Abstract

Value stream mapping (VSM) is a well-established method for analyzing production processes, material flow and information flow. Despite extensive benefits, conducting VSM manually is becoming inefficient and ineffective due to increasing production and product complexity. Concepts for digitally analyzing value streams have emerged addressing the issues of manual VSM. This paper aims to review existing scientific approaches concerning digitalized VSM in the context of manufacturing. The approaches are examined with regard to their practicality in the industrial context. Furthermore, the potential of employing process mining methods for digitalized VSM is discussed.

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Keywords: Value stream mapping; Process mining; Review

1. Introduction

Over the last decades, the demand for highly customized products increased continuously. In addition, growing global competition and the need to quickly adapt to customer requirements lead to frequently varying production processes[1]. To ensure efficiency, continuous analysis and optimization of these dynamic processes are crucial but challenging.

Value stream mapping (VSM) is a broadly applied lean management methodology that facilitates the analysis of value streams and the identification of opportunities for optimization. Essential process steps and key figures (e.g. throughput time) are visualized in a value stream map, which fosters the understanding of the actual as-is process and offers a medium for communication. Data is traditionally collected manually on the shop floor using pen and paper. This leads to time-consuming data collection and only allows to consider a snapshot of reality [2]. Due to these aspects, a beneficial application of conventional VSM is limited, especially in the context of frequently varying processes [3].

In parallel to the development of globalization and customization, continuous digitalization, especially induced through Industry 4.0 (I4.0), has led to the recording of extensive, granular production data. The deployment of such data to gain insights in production, e.g. through data mining, has already proven to be useful [1].

Lately, the use of digitally captured data for VSM is gaining attention with the goal of improving the economic feasibility in high variance production. Various data-based approaches for a dynamic VSM have been developed. Within these approaches, the use of process mining for VSM has been put forward by several authors. Process mining bridges the gap between data science (i.e., machine learning and data mining) and process science. It aims to discover, monitor and improve real processes by extracting knowledge from event logs [4]. Although the different approaches seem to be promising for an economical deployment of VSM, they are not yet established in manufacturing environments.

Therefore, the goal of this paper is to provide an overview of the state of the art of digitalized VSM, to examine the benefits of process mining for digitalized VSM and to derive current challenges that need to be met to establish process mining-based VSM in production. The remainder of the paper is structured as follows. In section 2, the state of the art regarding digitalized VSM is presented and examined.

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Section 3 discusses the relevance of process mining for digitalized VSM as well as chances and risks. In section 4, the areas of necessary action for the establishment of process mining-based VSM are identified. Section 5 summarizes the results and gives an outlook on future research.

2. State of the Art in Digitalized Value Stream Mapping

2.1. Methodology

Based on the guidelines for literature research in information system research identified by [5], the literature review follows three steps. First, the general literature scope is defined. This is followed by the literature search and analysis to identify relevant literature. The identified literature is reviewed and results as well as limitations are presented.

We limited the scope of the literature search to Scopus and the search space to article title, abstract and keywords. Only literature available in English or German was reviewed. The relevant search aspects and designated synonyms in the context of digitalized VSM were identified, yielding in the query string "TITLE-ABS-KEY ((digit* OR automated OR automized OR "Process Mining" OR "Industry 4.0") AND ("Value Stream Map*" OR "Value Stream Design" OR "Value Stream Method"))". The query returned 96 results. The titles of these results were examined for relevance. Throughout the examination process, results were excluded if they did not specifically address the value stream methodology or did not involve manufacturing. After the examination of titles, 43 relevant results remained. The abstracts of those were further examined for relevance, after which 28 results remained of interest. All 28 results were subject to a full text examination. After this examination, 22 results were deemed relevant.

The results deemed relevant after the full text examination are presented in 2.2. Additionally, following a forward search on authors, [6] was identified as relevant and included.

2.2. State of the art

The relevant reviewed literature can be distinguished in five categories: (1) Future viability of VSM in the context of Industry 4.0, (2) concepts for dynamic VSM and real-time monitoring, (3) integration of process mining, (4) integration of simulation, (5) focus on information flow.

2.2.1. Future viability of VSM in the context of Industry 4.0

Literature in this category examines the compatibility of I4.0 and VSM and assesses the significance of VSM within I4.0.

[7] conducted an empirical survey to assess the future viability of VSM in the context of I4.0 and digitalization. The authors concluded that VSM and I4.0 are compatible. The combination is considered capable of eliminating limitations of conventional VSM, such as incurring high efforts with regard to applying manual VSM in dynamic environments, and its static nature. [8] portrayed the same survey in more detail. Simulation, real-time data, updating with reduced effort, including data from MES and ERP and automated comparison between current and future state were identified as relevant further developments for VSM. Specific concepts for these developments were not provided.

[9] assessed the potential of combining various lean manufacturing tools and digital technologies. For VSM, the authors primarily identified potentials through increased data availability, providing information on equipment performance, production and object location. In addition, mapping of information flows, using continuous real-time data and simulating future state alternatives is enabled. Specific concepts were not provided.

2.2.2. Concepts for dynamic VSM and real-time monitoring

[10] presented an RFID-based sustainability-focused VSM approach, extending conventional VSM by environmental and social dimensions. The authors employed RFID systems to enable real-time VSM in an apparel company. Generated data is stored in ERP systems and analyzed in Excel files. Real-time tracking and reporting of essential figures in dashboards are enabled. The data transformation and utilization process were not further illustrated.

[11] introduced an approach to automatically analyze value streams based on mobile sensor networks. Physical locations of sensors and workstations are mapped and movement data captured by sensors are aggregated and used to calculate important key performance indicators (KPIs) (e.g. cycle time). Information on production processes and their sequence are manually captured. The presented integrated system architecture is highly customized. Details on the generation of the value stream map were not presented.

In contrast to the sensor-centric approaches, [12] focused on partly digitizing the data collection process for VSM with an application. The authors introduced an application for mobile devices that allows modelling the value stream digitally and capturing KPIs directly on the shop floor. Applying simulation techniques, different future state alternatives can be identified and evaluated. Limitations of VSM, such as capturing a snapshot in time and not providing real-time data, were not addressed.

[13] developed a dynamic value stream management (DVMM) concept. An integrated data model combines raw data from various sources (e.g. MES, ERP, sensors) and creates the data basis. The current value stream is analyzed in real-time and simulation and data analytics allow prescriptive analysis. The third element is an interface that provides information to the user. The authors did not state technical details on the presented infrastructure elements. A validation in form of a case study was not presented.

[14] proposed a dynamic VSM solution by assessing the combination of Industrial Internet of Things (IIoT) and VSM. A sensor-based efficiency monitoring system was introduced, allowing a dynamic and continuous monitoring of relevant KPIs. Both, the current value stream map and the future state value stream map are created manually by experts. It was not further addressed how to automatically derive a value stream map from digital data.

[15] introduced an I4.0-based real-time dynamic VSM approach to digitalize lean manufacturing. Integrated in a

framework, VSM creates the data foundation and interfaces the framework with both, the physical shop floor (e.g. based on sensors) and production planning data (e.g. ERP, MES). Details on how the data is collected and visualized were not discussed.

[16] presented an application (Value Stream Modeler), which focuses on graphical visualization, on a collaborative integration of workers, managers and experts and offers a single point of truth. Shop floor systems (e.g. MES) can be connected to integrate available information (e.g. KPIs). Data collection and deriving value stream maps from digital data were not further addressed.

2.2.3. Integration of process mining

[6] presented a data-assisted value stream method, which integrates cluster analysis, process mining and spread sheet calculations for value stream analysis and design. The authors proposed an (initially) hybrid methodology for conducting value stream analysis, which includes the conventional pen-and-paper approach as well as the process mining-based approach, to initially secure the correctness of the process model and related KPIs discovered through process mining. The method includes detailed descriptions of the procedure, including involved stakeholders. The method does not give insight into the required data basis and does not regard the derived process map as base for the value stream map.

[17] proposed a concept using process mining techniques to automatically derive a value stream model from data captured in IT systems. Conventional VSM is initially conducted to validate the digitally captured value stream. IT system-based VSM enables a continuous monitoring of the value stream while maintaining the well-known structure of value stream maps. While the proposed concept addresses and overcomes shortcomings of conventional VSM, it is not further clarified how process mining can be applied to derive the desired information. The concept was not validated.

[18] proposed a dynamic VSM approach on the basis of process mining. The authors argued that process mining can be utilized to analyze and visualize implicit process knowledge from transactional data automatically. To enable process mining-based VSM, relevant IT systems need to be identified (e.g. MES, ERP) and event logs need to be extracted. Process mining is applied on the event logs and value streams are displayed in near real-time. Information regarding the required data basis and implementation process is generic. The concept was not validated.

[19] proposed an approach to integrate process mining into conventional VSM to add an objective data-based perspective. The approach still relies on the conventional VSM, but enriches the process by supplying information on processes and KPIs obtained through process mining. This adds a neutral data-based perspective to the discussion of improvement potentials. Information regarding the required data basis and implementation process is generic. The concept was not validated.

[3] investigated the use of process mining methods explicitly for value stream mapping in internal logistics. The authors evaluated the processes using performance and conformance criteria to reveal different types of waste. Using different views, the types of waste can be examined by comparing target and actual processes, examining individual materials, and examining individual events across all products and processes. The types of waste examined were transportation, over-engineering, inventory and waiting. The authors concluded that the approach can be adapted for production.

2.2.4. Integration of simulation

[20] focused on a digital VSM approach in the environment of a simulation software, which allows for dynamic evaluation of the current state and optimized future states. First, a product family is selected and relevant data is collected. Then, the current state is modelled in the simulation software. Initially analyzing the value stream and collecting data is conducted manually.

As presented in section 2.2.2, [12] introduced an application for mobile devices that allows to model the value stream digitally and capture KPIs directly on the shop floor. For the simulation, the data captured within the application is then transferred to a simulation software, where different future state alternatives can be identified and evaluated.

2.2.5. Focus on information flow

Digitalization and increasing amounts of generated data emphasize the importance of information streams in production. In the following, literature on analyzing and assessing information streams with VSM in production is reviewed.

[21] presented an extended VSM method (VSM 4.0) to analyze the current value stream in terms of material and especially information flows. The authors extended conventional VSM to depict information logistic wastes and digital improvement opportunities. The proposed method still relies on manually collected data.

[22] focused on value stream design (VSD) considering the integration of new technologies (VSD 4.0). In addition to conventional VSD, opportunities to digitally enhance the material flow are considered and production and information flow are integrated.

[23] presented a holistic method for VSM 4.0. This method combines the already discussed VSM 4.0 for value stream analysis presented by [21] and VSD 4.0 presented by [22]. It was not regarded how digitalization and I4.0 affect the execution of VSM itself.

[24] and [25] further extended VSM 4.0 as proposed by [21]. [24] proposed a methodology for visualizing, analyzing and assessing information processes in more depth. [25] focused on added value and potentials of I4.0 technologies in value streams. The authors combined and extended VSM 4.0 with other approaches to achieve a more precise representation of data and information flow. On this basis, a future state including improvements in material and information flows with focus on I4.0 technologies can be designed.

[26] presented a procedure to harmonize information flows to control operational processes and achieve the required quality. New symbols to illustrate and assess information quality in value stream maps are introduced.

[27] discussed approaches for integrated and lean information streams in production. Lean information processes aim for a continuous improvement by reducing waste. An adapted VSM method, which captures all directly and indirectly supporting documents and information processes relevant for production, was presented.

2.3. Implications and limitations of the state of the art

The reviewed literature indicates that digitalization in production and its implications on VSM is addressed in various ways. Literature either focusses on (1) the viability of VSM in the context of I4.0, (2-4) approaches for (partly) digitalized VSM or (5) the extended examination of information flow.

Literature from the first category supplies the motivation for the topic and relevant fields of research, but no specific approaches for combining VSM and digitalization.

Literature regarding a more detailed examination of information focuses on emphasizing information flows in value stream maps, especially to identify improvement potentials through I4.0 technologies. Literature in this category extends conventional VSM approaches to account for these aspects, but not to conduct digitalized VSM.

With regard to literature presenting digitalized VSM, diverse approaches could be identified. However, approaches not based on process mining are either in concept phase ([13]) or propose hybrid solutions, where the mapping itself is not regarded, but IT systems are integrated to monitor or simulate various characteristics of the value stream ([14–16]). Only approaches focusing deploying process mining for VSM (e.g. [6]) address the use of digitally captured data to automatically derive process knowledge. The latter, production-focused approaches have not yet been validated and do not supply details regarding the required data basis. The most elaborate concept in the context of production is presented by [6].

Based on these findings, the relevance of process mining for digitalized VSM is examined in the next section.

3. Relevance of process mining for digitalized VSM

3.1. Advantages of process mining for VSM in manufacturing compared to other digitalized approaches

As the literature research has shown, numerous approaches for digitalized VSM exist. Approaches not based on process mining fail to consider VSM activities holistically. The advantage of process mining-based approaches thus lies in the simultaneous integration of the tasks of mapping processes and monitoring KPIs, which is inherent in process mining as such. Additionally, process mining-based approaches focus on the use of readily available data from MES and ERP systems, instead of requiring the use of dedicated sensor-systems or manually collected data. The compatibility of process mining and VSM is discussed in detail in the following.

3.2. Potential combinations of process mining and the value stream methodology

In the following, we identify beneficial combinations of process mining types and VSM activities and give an overview of these combinations (cf. 1). Generally, three types of process mining are distinguished: Discovery, conformance and enhancement. Discovery aims to generate a process model based on an event log without using a-priori information. Conformance compares an existing process model to the reality captured in event logs to detect and explain deviations. Enhancement aims to improve an existing process model on the basis of information recorded in the event log [4].

Additionally, clustering as a method closely related to and partly enabled by process mining is assessed for potential areas of combinations. Promising areas of combination are marked in black and are described in the following.

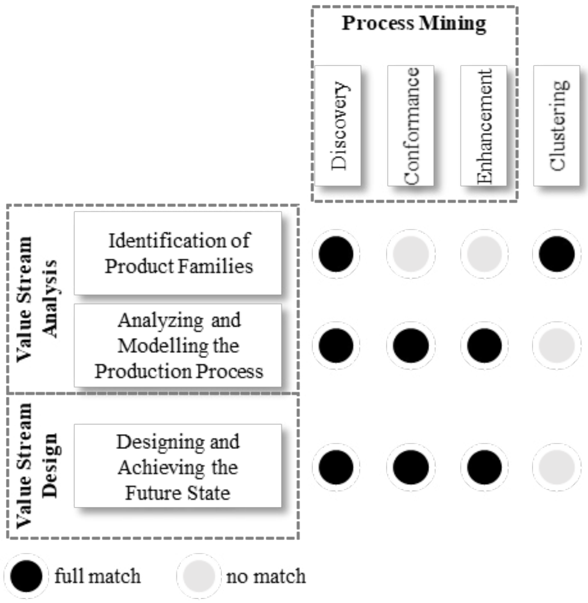

Fig. 1. Combinations of process mining and VSM.

Integrating process discovery and/or clustering technologies into product family identification reduces the required efforts for such an identification. Within VSM, product families are identified to narrow the scope of VSM. By applying process discovery, this generalization becomes in principle dispensable with regard to economic feasibility. Automatically extracting process knowledge from transactional data allows capturing information about all product variants simultaneously and aggregating it accordingly at little to no added cost compared to doing so for one variant.

A meaningful grouping of products into product families is nevertheless still highly relevant and beneficial for process analysis, visualization, improvement and future state design, especially in the context of high-variance, low-volume production. Building product families allows to focus efforts of involved stakeholders at all stages of VSM. Clustering techniques substitute conventional, time-consuming product family identification methods. Based on either event data or master data, they allow to group cases according to process similarity or other characteristics. For product family clustering based on event data, trace clustering can be used. Here, to identify process variants, sets of similar log traces can be grouped. For product family clustering based on other master data, density-based as well as proximity-based clustering algorithms have shown to be useful.

Potentially the most important and most discussed combination of process mining and VSM is with regard to analyzing and modeling production processes, i.e., the value stream. Process discovery methods allow for an automated analysis and mapping of processes based on transactional data in near real-time. A continuous and holistic analysis of production processes is enabled. In this context, process enhancement methods allow to extend event logs with information on performance- and resource-related information. This enables further performance analysis and calculation of KPIs (e.g. processing time). Furthermore, process conformance methods allow identifying potential discrepancies between the digitally captured processes and expected processes.

An integration of process mining techniques into VSD offers potentials for identifying improvement opportunities, designing an ideal future state as well as monitoring the transformation of the current state to the future state. Process discovery and enhanced process models create the basis for the identification of inefficiencies and designing an ideal future state. Process conformance techniques can be used to assess and quantify process similarity of the current and the future state. Deviations and undesired process flows can be identified and addressed accordingly. The impact and effectiveness of measures can be tracked in near real-time.

3.3. Chances and risks of process mining-based VSM

Risks addressed in the reviewed literature can be divided into risks associated to data and methodology.

Methodology risks target the automated generation of value stream maps. The absence of manual practices may decrease the acceptance of results and confidence in the model. Additionally, a digital approach contributes less to understanding and experiencing processes firsthand. Approaches should thus always include stakeholders throughout all phases.

Data-related risks can be adopted from general risks of process mining in production. The quality of results depends on data availability and quality. The scope and completeness of analyzing production processes is limited to the data present in the system. Consequently, excessive data collection on the shop floor is needed (e.g. via terminals or sensors), which results in heterogeneous system and data landscapes and thus in challenges in connecting the data. Furthermore, manual work remains difficult to track. Terminals for employees to manually enter information, which is especially apparent in assembly, pose the risk of incorrect and incomplete information. Low-level data, generated by sensors, pose challenges in the context of noise and handling large data volumes. Ultimately, data loading time delays of MES and ERP-systems obstruct real-time tracking of production processes. Most of the data-related risks can be proactively addressed (e.g. with systematic process changes).

Direct benefits of combining process mining techniques and VSM were discussed in section 3.2. Integrating process mining into VSM allows countering the static nature of conventional VSM. Yet, process mining not only has the potential to make the VSM methodology as-is more efficient, but may also make it more effective by extending the methodology. As suggested in [17], process mining in the context of value streams can also be used to identify problems with the supply of information from IT systems. [28] show that process mining in value streams can be beneficial as basis for simulation activities. [29] suggest the combination of process mining and machine learning for lead time prediction based on process data from production to improve planning activities. Furthermore, [30] suggest mining event data to determine variant-specific process costs.

4. Necessary areas of development to facilitate process mining-based VSM

Based on the limitations of the state of the art, the identified potential combinations of process mining and VSM as well as the chances and risks, various areas need to be addressed to establish process mining-based VSM in practice: (1) data requirements and methodology, (2) visualization and (3) extension of the VSM methodology.

The first and most pressing area is required data for process mining-based VSM. It has to be defined, which data is actually required for the chosen analysis, as well as how the data can be derived, cleaned and combined into a process data model. The definition of required data is challenging due to heterogeneous systems in different companies. From experience with practitioners, it seems expedient to specify the measurements needed to define the value stream and respective KPIs and to identify relevant tables in the individual systems based on this. Furthermore, a methodology for deriving and combining case IDs has to be established, which allows the distinct tracking of products composed of different modules.

The second aspect concerns the visualization of value streams in process mining-based VSM. A key role of VSM is the visualization of complex value streams. Here, the target is to create a value stream map as a simplified and functional pictorial representation, which can be easily understood even without a detailed background knowledge [31]. So far, process mining applications depict processes through different modelling notations, such as Petri nets. In order to supply the same information as through the value stream connotation, available process mining software must be adjusted accordingly. Here an assessment including VSM practitioners should be carried through to challenge, which connotations are really required and to which extent they have to be automatically derived through process mining.

The third aspect concerns the extension of the VSM methodology. As described in section 3.3, process mining-based VSM can be extended through the application of further data mining and machine learning methods, e.g. for the prediction of lead times. Such use cases have to be identified and should be assessed with regard to their value by practitioners. Additionally, and with regard to one of the most pressing issues of our time, the climate crisis, we urge the extension of the process mining-based VSM to also consider ecological and social sustainability criteria. Sustainability-focused VSM has been introduced approx. 20 years ago and has received much attention ever since (e.g. [10, 32]). The combination of these topics lowers barriers for companies to start measuring sustainability with regard to production and can create a competitive advantage with regard to customer satisfaction and upcoming regulations.

5. Conclusion and outlook

In this paper, we provided an overview of the state of the art of digitalized VSM research and evaluated the potential of combining process mining and VSM. We showed that process mining supports VSM especially in analyzing and modeling the production process and greatly reduces efficiency challenges in conventional VSM. Nevertheless, for a fully comprehensive combination of process mining and VSM, challenges in the areas of data requirements, methodology, and visualization still need to be solved. For further research, it is precisely these challenges that lend themselves to the development of new approaches. It is important to investigate the extent to which process mining can be used to reduce the focus on individual product families in VSM. Additionally, sustainability-focused extensions of the VSM methodology must be considered during the development of digitalized VSM methodologies to place greater emphasis on sustainability factors in production.

For future research, we plan to examine useful definitions of the required data basis for process mining-based VSM that also allows to assess sustainability.

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