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Smart Risk Analytics Design for Proactive Early Warning

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Purpose: Automobile manufacturers are highly dependent on supply chain performance which is endangered by risks. They are not yet able to proactively manage these risks, often requiring reactive bottleneck management. A proactive and digitalized early warning method is needed.

Methodology: The publication provides methodological-empirical contribution to proactive early warning resulting in a smart risk management approach. The methodological approach is carried out according to the design science research approach.

Findings: The developed smart risk management enables an automated, objective and real-time ex-ante-assessment of supply chain risks in to secure the supply of the automobile manufacturer. Smart risk analytics based on artificial intelligence is shown with its suitability for proactive early warning using the example of inaccurate demand planning.

Originality: The analytical approach provides insights into the flexibility of supply chains under risk and the impact over time, which is applied in the proactive early warning design. Artificial intelligence is applied to predict and assess supply chain risk events.

Keywords: Supply Chain Risk Management, Proactive Early Warning, Smart Risk Analytics, Machine Learning

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1 Motivation

The profitability of automobile manufacturers (original equipment manufacturers, OEMs) highly depends on the reliability and performance of suppliers and supply chains (SCs) due to e.g. outsourcing, lean management and low inventory levels (Khan, 2018, pp. 141). The value added in the automobile industry originates by 30 percent from the OEM and by 70 percent from the SC (VDA, 2018). Therefore, the monitoring of supply chain risks (SCRs) which endanger the performance of the SC is of great relevance to OEMs.

An ordinary car consists of about 5000 parts (Kırılmaz and Erol, 2017, p.62). Most parts are provided by a large number of suppliers. This implies complex SC networks, which require considerable planning and control effort on the one hand and are prone to significant risks on the other hand.

These SCRs may be classified as internal process and control risks, supply risks, demand risks and environmental risks (Christopher and Peck, 2004, p. 10). However, OEMs are not yet able to fully manage these risks proactively. Currently, this implicates a reactive bottleneck management in the event of disruptive risk impacts. There is a need for a scientific method that supports a more proactive management to avoid or minimize the risk impacts and can be implemented easily in practice.

SCR impacts can be classified as financial, performance, operational, demand, informational, relational, hybrid and other (Oliveira, et al., 2019 p. 24). Economic impacts are connected to cost, profit and revenue and operational impacts are related to e.g. stockouts, reliability, capacity, which are features of the processes (Oliveira, et al., 2019 pp. 24). Financial impacts in the automobile industry are for example an increase in procurement costs or an increase in transportation costs (Kırılmaz and Erol, 2017, p.62). One missing part in car production can lead to delays (Lopez and McKevitt, 2017). The protection of assembly lines from delays due to missing parts, which is one aspect of SCR impacts for automobile manufacturers, is an important concern. A stopped assembly line leads to high costs in the dimension of more than $ 100 million per day of production breakdown (Kırılmaz and Erol, 2017, p. 61). In the worst case, SCRs lead to a complete production shutdown of the OEM, which is associated with immense costs (Khan, 2018, p. 141). For example, BMW had to stop the production of several models in summer 2017, as first tier supplier Bosch was unable to supply steering gears (Lopez and McKevitt, 2017). The reactivity of existing methods to manage SCRs at the OEM poses a challenge with regard to the high impact of the risks, the limited possibility to predict potential losses and the lack of opportunities to act. In result, due to the high dependency on SC performance, the variety of highly specific parts, the complexity of global SC networks and the immense damage caused by supply risks, the proactive management of fluctuations in demand planning is of crucial importance in supply chain risk management (SCRM). Digitalization is expected to further increase the availability of data in SC networks. Through the application of suitable technologies such as data mining (DM), big data (BD), machine learning (ML) and artificial intelligence (AI), risks can be detected and controlled more quickly (Schlüter, Diedrich and Güller, 2017). DM, ML and AI technologies provide new opportunities for early warning in SCRM to turn data into correlation and new knowledge.

Consequently, this contribution focusses on the supply risks resulting from inaccurate automotive demand planning and the opportunities which arise through the new technologies of ML and AI for SCRM.

The developed methodological-empirical contribution to proactive early warning is subsumed into a smart risk management approach. The methodological approach is carried out according to the design science research (Hevner, 2007). It results in a scientific concept which applies ML and AI technologies on empirical company data for demonstration and evaluation. The underlying potential for automatization and assistance supports the proactive SCRM and underlines the practical relevance.
This paper proceeds as follows: Chapter 2 reviews automotive demand planning, early warning and SCRM, which provides a basis for the paper. Section 2.3 summarizes the need for proactive early warning and design requirements. In chapter 3 the smart risk analytics design for proactive early warning is developed. Demonstration and evaluation is presented in chapter 4 based on empirical company data. Finally, a discussion and conclusion is presented within chapter 5.

2 State of the Art

2.1 Automotive Demand Planning

In build-to-order production, demand planning is a key component of the order management. The automotive demand planning is situated between the conflicting priorities of supporting maximum demand flexibility and long-term stable control of supply. Demand flexibility is needed for the realization of technical trends and customer requirements. At the same time, a long term stable control of supply is required because of the long lead times in global SCs and the high degree of product specialization. Rolling demand planning is followed by capacity planning to ensure that suppliers can deliver the demands within the scope of a certain contractually agreed flexibility (Volling and Spengler, 2011; Volling, et al., 2013). In order to secure the supply of the OEM, a long-term pre-planning of customer orders and market demands is carried out. Later on, SCs are controlled on the basis of delivery call offs to first tier suppliers. Rolling demand planning is used to achieve accurate control of supply for volatile demands in global customer markets. A more detailed description of the process can be found in Gehr and Hellingrath (2006, p. 52). A study conducted by IBM / Aberdeen suggests that a rolling forecast improves the accuracy in comparison to a less static process by roughly 14 % (Cavicchi, 2018, p. 4).

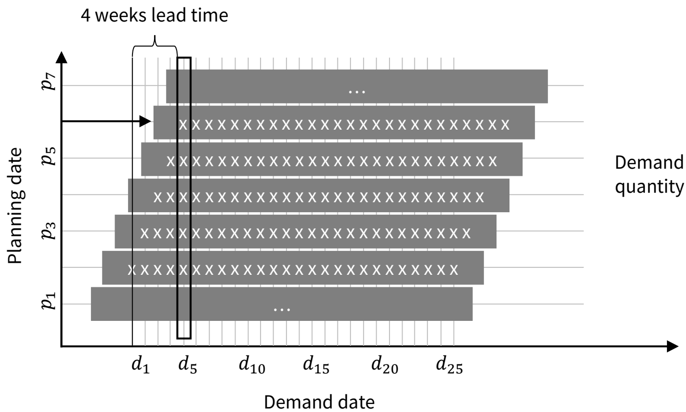

Figure 1: Data in the Rolling Process of Automotive Demand Planning

An example of the availability of demand planning data in relation to the demand date in a rolling process is depicted in Figure 1. Every horizontal line represents a planning stage of the demand quantity with regard to a specific demand date (x-axis). Until the demand date is reached, the demand quantity is planned on a weekly basis.

The pre-planned demand may differ significantly from later occurring actual customer orders, for example due to unexpected volumes of volatile, global sales markets and technological trends. The great variety of selectable car equipment results in an immense planning complexity (Thun and Hoenig, 2011, p. 244, Harland, Brenchley and Walker, 2003, Tang and Musa, 2011, p.28). According to a study, the top challenge relating to SC flexibility is the demand volatility and poor forecast accuracy with 74 % (Geissbauer and D'heur, 2010 p. 4). The risk of change in customer demands is assessed as high impact high probability in the automobile industry (Thun and Hoenig, 2011, p. 246). If the demand changes, a certain flexibility of the SC is required to ensure the ongoing supply of the OEM. Flexibility is an individual attribute of every SC. Beyond that, if flexibility is exceeded because of inaccurate demand planning, further fluctuations in demand may lead to the significant, internal risk of insecurity of supply. Demand uncertainties arise frequently in volatile automobile sales markets. This requires high flexibility of the SC to adapt the production volume or the production product mix, in order to counter demand uncertainties with volume flexibility (Thomé, et al., 2014, p. 102).
Hence, demand risks arise for example from uncertainties in demand forecasts, which in turn might result in delivery bottlenecks (Thun and Hoenig, 2011, p. 244). The customer risk of placing orders (Harland, Brenchley and Walker, 2003) is part of this risk of inaccurate demand pre-planning. The demand risk can be differentiated into volume mismatch and mix mismatch (Ceryno, Scavarda and Klingebiel, 2014, pp. 5, pp. 11)
In order to avoid the risk of inaccurate demands, Thun and Hoenig, 2011 recommend a focus on secure sales markets and on a small number of variants with as little as possible demand volatility (Thun and Hoenig, 2011, p.

245). However, this is no option for German OEMs due to their position in highly competitive sales markets and their focus on high variety as a key selling argument. Furthermore, customer preferences necessitate regionally tailored product variants(Geissbauer and D'heur, 2010 p. 2), which is increased by legal requirements.

The key figures forecast quality key figure (FQ) and the tracking signal (TS) describing the quality of automobile demand pre-planning and the respective over- or underestimation have been defined by VDA (2008). FQ describes how the forecast demand quantity, marked in Figure 1 by the black frame, has matched the later occurring real demand in the retrospective. TS describes the over- or underestimation of the demand in quantity (VDA, 2008). Both key figures may be applied usefully in a proactive SCRM approach.

2.2 Early Warning and Supply Chain Risk Management for Automotive Demand Planning

In the context of this publication, the understanding of proactive SCRM is aimed at preventing or minimizing the damage caused by risk events, while the structure of the automotive SC remains unchanged. The need for proactive SCRM, especially in the automobile industry, has already been recognized as a relevant issue in the academic field some time ago (Henke and Besl, 2008). Nonetheless, there is still a lack of suitable models and methods which support OEMs to proactively manage SCRs.

The basic idea of proactive risk management using big data technology is shown by Leveling, Edelbrock and Otto (2014), but there is still a considerable need for research on design and conception. A proactive planning procedure is proposed by Kırılmaz and Erol (2017) for shifting orders among suppliers to mitigate supply risks. Yet, this approach is unsuitable in the case of single sourcing, which often occurs in the automobile industry, because demands cannot be distributed to other suppliers. Risk monitoring has received the least attention (Ho, et al., 2015). This leads to a research need on early warning monitoring systems and their empirical validation (Ho, et al., 2015). SCRM solutions do not yet provide a sufficient time period for taking measures against the risk impact, require very high manual effort, and do not yet provide sufficient specific information on forthcoming risk events. This leads to the need to provide better information and more assistance for a proactive SCRM. An increasing amount of data is available in the company, but there is currently a lack of suitable methods which take advantage of this data in SCRM.

The main objective of early warning is the evaluation and transmission of information on already latent present risks in an early stage, leaving enough time to plan and initiate response strategies and actions. The differentiation of scientific approaches can be made with regard to the available time period to act, the reliability of the warnings and the automation of the transfer of the warnings into existing information and management systems.

An approach for early warning systems has been developed by Moder (2008): this approach is based on questionnaires and lacks technological aspects of digitalization for automatization, quantitative assessment and real-time capability. The evoluionary stages of early warning have been described by Moder (2008) in three generations (Moder, 2008 p. 22): (1) key figures, (2) indicators, (3) weak signals. This distinction supports the view of a more reporting based approach as given by descriptive analytics. Nev-

ertheless, even these approaches are usually limited to critical commodities in practice. Because of the considerable effort involved, thus, a SCR monitoring of all suppliers is currently not possible (Meierbeck, 2010).
The earlier a risk event with a relevant impact is identified, the more time is available to initiate appropriate measures in the SC to minimize its impact, and the better the chances of success (Henke, et al., 2010). Especially the aspect of providing a sufficient time period to react represents a methodological challenge.

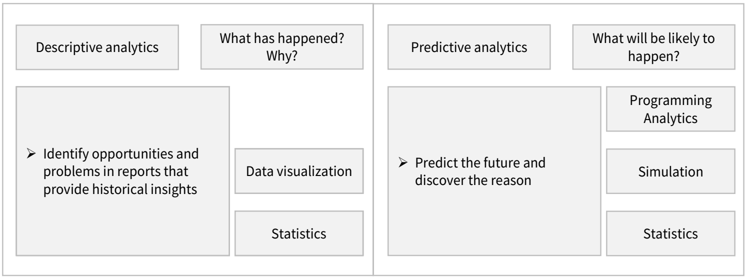

Figure 2: Descriptive and predictive analytics

Figure 2 distinguishes descriptive and predictive analytics based on Tiwari, Wee and Daryanto (2018) Fi. Business intelligence (BI), Analytics, BD, ML and AI methods are increasingly being discovered for supply chain management (SCM) to give valuable insights (Addo-Tenkorang and Helo, 2016; Arunachalam, Kumar and Kawalek, 2018; Tiwari, Wee and Daryanto, 2018), but there are currently only few research approaches for SCRM and early warning. In SCM the focus is shifting away from risk reports to assistance systems. The need for risk information has been researched by Fan, et al., 2017.

The availability and timely utilization of SCR information is extremely important and deserves more research (Fan, et al., 2017). The applicability of predictive analytics for supply risks is shown in general by He, et al. (2014). Traditional descriptive approaches for early warning apply e.g. balanced scorecards or questionnaires (see for example Czaja (2009)), having a descriptive function. Material flow simulation can be applied for similar time periods of transportation times (see for example Hotz (2007)). For longer periods of early warning, new approaches using analytics need to be developed. Predictive analytics approaches can be classified into machine learning techniques and regression techniques. Machine learning techniques are applied due to their performance in handling large-scaled datasets with uniform characteristics and noisy data (Nassif, et al., 2016 p. 2153).

2.3 Summary

Existing scientific approaches for early warning lack information on the risk cause and effect and do not provide sufficient time to react in order to minimize the risk impact. Furthermore, the prediction of the exact time period, i.e. demand date of the OEM, is not sufficiently included in early warning. So, it is difficult to identify the periods in the production program which is threatened by risk impacts regarding security of supply.

A suitable method for providing risk information at an early stage is required. This would support OEMs to follow a proactive SCRM approach in order to mitigate risk impacts. Considering industrial practice, the main target of the early warning should be the security of supply of the OEM in order to depict the connection between the risk cause and the impact of the risk. The approach should provide a sufficient time period to react before any risk impact on security of supply occurs. Furthermore, it should provide information about risk cause and effect in order to choose sustainable, cause-related actions to minimize the forthcoming risk impact.

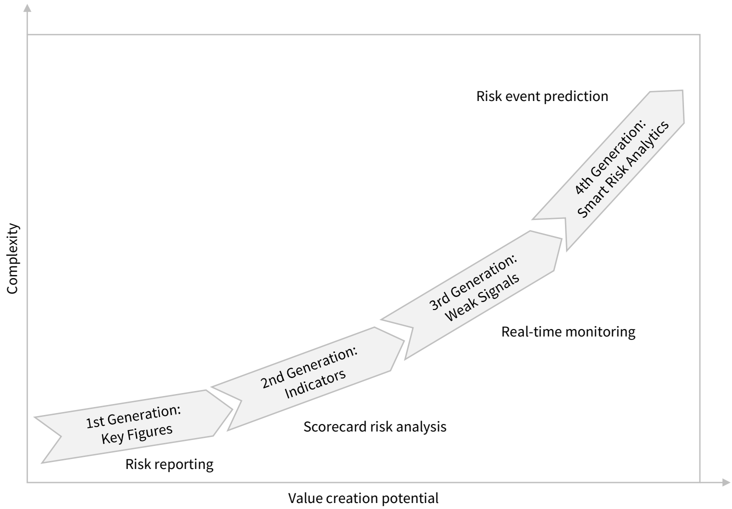

Figure 3: Stages of Evolution in Early Warning

There is a need for research in the field of the methodological-technical design in order to meet these requirements. For the development of the design approaches from digitalization and the field of ML and AI can be used. A systematic approach for DM, ML and AI application in early warning is needed to advance the quality of early warning and to reach a new level of assistance. Here, the data, which is increasingly available in the course of digitalization and currently do not add any value to SCRM, should be applied to generate new risk knowledge. The three stages of early warning described by Moder (2008) can be extended by another level for automatization, improved reaction time, reliability of information and completeness of included suppliers, visualized as smart risk analytics in Figure 3. In the following, this smart risk analytics approach has been technical-methodological designed.

3 Concept

There is a variety of SCRs that can affect the SC performance and thus the security of supply of an OEM. The aim of the concept is to forecast the security of supply as the key target, i.e. KPI, of early warning for application in an assistance system. The security of supply describes the availability of the parts required by the planned production program according to the planning and control processes of the OEM. The methodological design of proactive early warning is developed on the example of the SCR of inaccurate automotive demand planning. In order to make sustainable decisions regarding proactive SCRM actions, specific risk event information is needed at an early stage. This information will allow early action to prevent or minimize risk impacts, costs and supply bottlenecks of the OEM in the given action time (cf. Figure 4).Sufficient reaction time is an elementary factor in proactive SCRM.

The smart SCRM design aims to secure existing SC networks against risk impacts in an event-oriented manner. At the same time SC structures are not changed by measures for risk prevention or impact minimization due to economic opportunities and despite the risk liability of these structures. Executing proactive SCRM requires an information provision, which is fast, on-time, reliable and dynamic, to render assistance for management decisions.

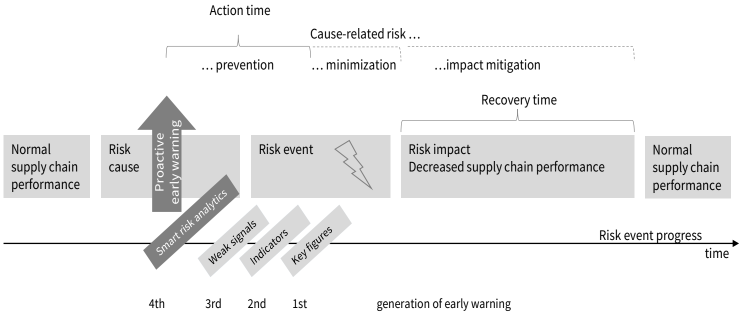

Figure 4: Proactive early warning at the risk event progress

Proactive early warning enables a reaction to forthcoming risks as visualized in Figure 4. For the smart SCRM design proactive early warning is an elementary module. Proactive early warning provides the action time period to prevent or minimize the risk impact. The design is thus geared to recurring risk events. The methodological-technical design of proactive early warning, called smart risk analytics (SRA), is introduced hereafter. The design follows the early warning requirements described in chapter 2.3.

In advance of proactive early warning, the identification of the SCRs of the OEM is required. This is followed by the prioritization of the risks that - due to recurring events - are of relevance to the OEM and should be included in the proactive early warning.

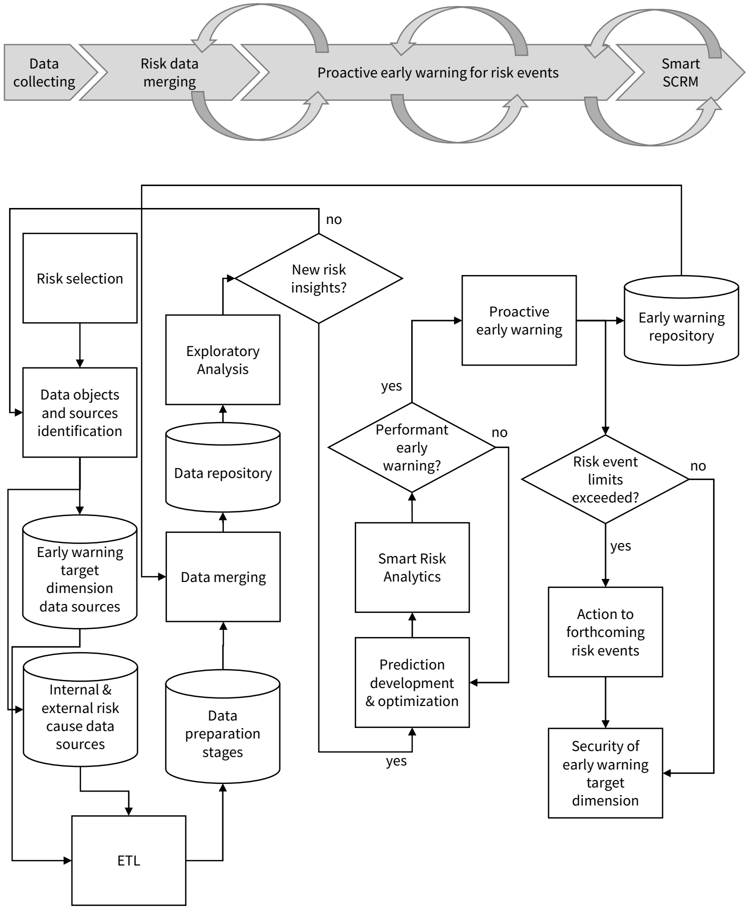

Figure 5: Processing Architecture of the Smart Risk Analytics Design

The processing architecture is visualized in Figure 5 and contains three iterative cycles. The agile approach allows to incorporate findings from one cycle into another cycle and thereby improve the quality of early warning.
The first iterative cycle (cf. Figure 5) describes the explorative analysis of risk cause and risk impact. The data basis is compiled (extract, transform, load - ETL) from internal and external data sources on risk causes and KPIs for the early warning. Data preparation is a core process for SRA and includes assessing the raw data from the original data source and converting the data into a risk data repository. Iteratively, the data basis can be expanded and the analysis repeated, so that the results may be used as a knowledge basis for the continuous improvement.
The second iterative cycle (cf. Figure 5) is applied for the SRA model development. The core of the SRA design is a forecast algorithm. Here, algorithms are trained by application on historical data of risk causes and targeted KPI. Hereby the algorithm learns the patterns and interrelations between the variables in the analyzed demand planning processes.
Applicable algorithms for SRA are decision tree, random forest, support vector machine, k-nearest neighbors, regression and artificial neural networks (cf. Backhaus, et al., 2016). A more detailed discussion of these algorithms is carried out in chapter 4. The algorithm should be selected based on performance and optimized regarding its features and parameters. The performance should be streamlined according to the early warning criteria, which are to be distinguished from the usual data mining criteria. With regard to the early warning application, incorrect warnings are to be avoided at all costs, even at the expense of missed correct alerts, as they lead to a loss of user confidence in the solution. The dynamic effects of risk causes on KPI representing the security of supply are mapped by ML or AI.

The algorithms are to be individually selected and trained for each SC as the lead time of the SRA has to reflect the SC specific dynamic risk behavior. Feature engineering is used for the development of KPI represented in risk cause data. Key figures serve as condensed input from the original process data for the algorithm. For optimization of prediction within SRA, feature engineering, feature selection and parameter optimization has been conducted for the mentioned algorithms and the performance has been compared for all algorithms. The methodological-technical design requires an iterative development and an specific implementation for each risk and for each supply chain.

The third iterative cycle (cf. Figure 5) allows the application of the trained algorithms on new data for a proactive early warning. Furthermore, all data and results are stored in a data basis in order to continuously improve the SRA. The proactive early warning for risk events can be bundled and controlled in an event-based manner in the smart SCRM. In a cloud solution, the smart risk analytics service for early warning, can be used by OEMs as well as suppliers.

4 Demonstration

For the demonstration, the concept has been implemented prototypically. By using empirical company data of an automobile manufacturer, the functionality of SRA for proactive early warning can be demonstrated. The demonstration is carried out according to the reliable and reproducible Cross-Industry Standard Process for Data Mining (CRISP DM), which asks to analytically apply, demonstrate and evaluate the concept. The CRISP DM consists of six phases, which are not run sequentially, but repeatedly in an iterative manner. The phases are (1) business understanding, (2) data understanding, (3) data preparation, (4) modeling, (5) evaluation and (6) deployment (Chapman, et al., 2000). Iterative steps are possible between all the phases, in particular between (1)-(2), (3)-(4) and (5)-(1), which allows the integration of new insights into the development. For more in-depth information about CRISP DM, please refer to suitable literature such as Chapman, et al. (2000) and Wirth and Hipp (2000).

The extent of the data basis for the demonstration is shown in Table 1. The data basis contains of a variety of part families, part numbers, demand planning dates, demand dates and demand planning values. The availability of the demand planning data for the SRA depends on the lead time of the early warning forecast in comparison to the actual time of the OEM's demand (see Figure 1). This results in the dynamic KPI calculation depending on the lead time for the SRA. The explorative analysis is conducted on the data repository for correlation analysis, and visualized in Figure 6.

Table 1: Objects of the Data Basis for Smart Risk Analytics Demonstration on the Risk of Inaccurate Demand Planning

Object Classes	**Objects**	**Data Basis**
Early warning target KPI	Security of supply	303.288 values (4 key figures for each part number and demand date)

Object Classes	Objects	Data Basis
Supply information	Forecast date Forecast period Lead time of planning Demand planning date (p_n) Demand date (d_n) Demand values Actual demand	October 9, 2017 to March 29, 2019, 76 planning dates within 1,5 years Forecast period of 26 weeks 1.971.372 demand values 371 days of production 75822 actual demand values
Demand information	Supply chain 1st tier supplier Part number Part family name	39 supply chains and 1st tier supplier 312 supply parts (differentiated by part numbers)
Features	Demand planning key figures	7.051.446 values (93 key figures calculated for each part number and demand date)

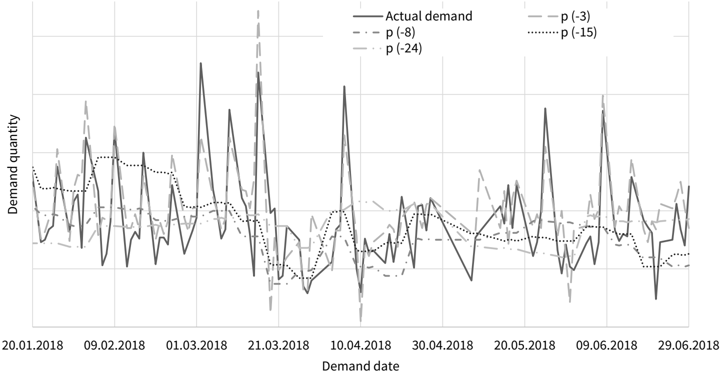

Figure 6: Explorative Analysis of Demand Planning Data

In feature engineering a variety of key figures have been defined and 7.051.446 values have been calculated. The subsequent feature selection allows the identification of relevant features depending on the algorithm. Features have been identified for each algorithm and part family for an optimization of the SRA. The demand planning forecast accuracy (FQ) was analyzed depending on the part family of the respective SC. The analysis of the forecast quality of the OEM has shown that the quality (FQ, TS) varies depending on the parts considered. A distinction can be made for e.g. part families or low-runner and high-runner.

The selected algorithms map the interrelation between automotive demand planning as the risk cause, the spread of risk and the risk impact on the KPI representing the security of supply of the OEM. The algorithm applies the trained risk behavior and can predict when and how strong a risk impact may occur based on a certain risk cause. The behavior is to be determined for each SC and can be described as SC dynamic under risk. The dynamic behavior is depending on, among other things, safety parameters, transportation times, replenishment lead times and production times.

In the demonstration of the developed models according to Figure 5, it could be shown that the quality of the prediction of the KPI security of supply strongly depends on different demand planning dates and on the respective SC and its flexibility. This leads to different time horizons for proactive early warning. Accordingly, for the suitability of the concept, no general statement about the time horizon of proactive early warning can be made for all SCs. The dynamic behavior of the respective SC results for example from technical characteristics of the products, production and transport processes. The performance of SRA depends on the SC, the planning and procurement lead times of suppliers. Nevertheless, the resulting reaction time provided by the concept is usually up to several weeks and results from the SC's individual time horizon of proactive early warning. In addition to the function of proactive early warning, the concept also provides knowledge through insight into the flexibility of suppliers and SCs for the various products. It allows the identification of SC-specific flexibility depending on the planning cycles in demand planning.

The results of SRA are shown exemplarily in Figure 7. Similar to the classification of FQ (VDA, 2008, p. 15), limit values for the early warning risk score must be determined to distinguish between a low criticality and a high criticality which requires action. This is visualized by the dashed line. The limits of the classes should be based on the risk tolerance of the OEM. The results of SRA show the potential for dynamic risk assessment and dynamic proactive early warning by digitalization of SCRM using technological designs.

The resulting prototypical implementation has allowed a demonstration but also an assessment of applicability in practice. The demonstration has proven that the SRA concept is well suited for risk assessment and risk forecast related to the risk of inaccurate demand planning and generation of proactive early warning. Furthermore, an objective and quantitative assessment and of the expected risk impact including its timing is possible.

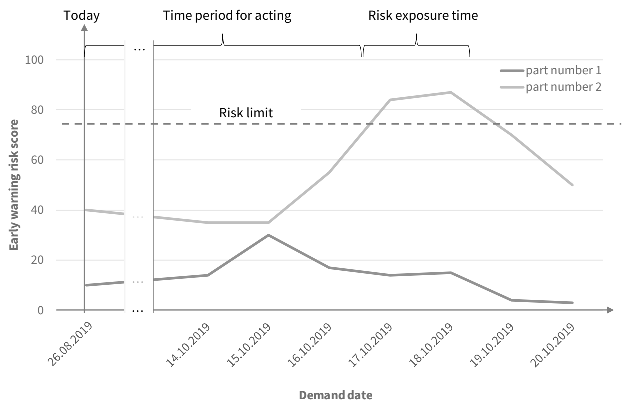

Figure 7: Smart Risk Analytics Result: Proactive Early Warning

The concept was demonstrated in its suitability for operational (short term, 0 to 2 weeks) and tactical (medium term, 3 to 8 weeks and long term 9 to X weeks) planning horizons (cf. VDA, 2008, p. 15). Accordingly, the technical concept of forecasting extends traditional approaches with regard to the available time horizon for reaction.

5 Conclusion

The SRA concept enables the objective assessment and forecasting of forthcoming risk events in an risk-cause-related proactive early warning. The concept can be technically implemented with a high degree of automatization for information and management assistance in the practice of OEMs.
The proactive early warning on the specific date of demand, which is threatened by SCRs, allows sustainable measures and collaborative management in the SC. SRA is shown with its suitability for proactive early warning using the risk example of inaccurate demand planning by application of the concept to OEM company data. Previous challenges of implementation in practice can be solved with this concept, which shows a way of digitalization in early warning and SCRM based on AI and ML to SCR data.
The analytical approach provides new insights into the flexibility of SCs under risk and the impact of risks over time. A new area of digitalized, real-time and objective proactive early warning is opened up by the concept.
For supplying automobile production with products from worldwide SCs, these supplies need to be protected against a variety of risks. Smart SCRM provides a solution to proactively secure the supply of the future production program. Depending on the risk and possible proactive measures, various company divisions of the OEM – from logistics, procurement and program planning to sales and finance - may be involved in the smart SCRM. Furthermore, the processes and organizational structures across the departments (logistics, procurement, finance and more) can be aligned to the more anticipatory reaction rather than reactive bottleneck management. The approach follows the digitalization paradigm and demands for new

competences of the employees. Due to the increasing complexity of the developed 4th early warning evolution stage, it is necessary to combine expert knowledge in SCRM and AI in the OEM's department.

The transferability of the concept to other OEMs is allowed by individual training of the algorithms on the respective SC. The further digitalization of SCs and business processes progresses, the more potential for SRA emerges and allows for the methodological concept to be expanded by taking on additional SCRs.

As it is known from other AI research projects, the generation of a suitable data basis requires a considerable amount of effort. For the sustainable application of AI in the company, the availability of data, the period of data storage and the resistance to use must be considerably optimized on the course of digitalization. Further research is needed on the assistance and automatization of optimized reactions to secure the supply against risk impacts within the smart SCRM concept.

References

Addo-Tenkorang, R. and Helo, P. T., 2016. Big data applications in operations/supply-chain management. A literature review. Computers & Industrial Engineering, 101, pp. 528–543.

Arunachalam, D., Kumar, N. and Kawalek, J. P., 2018. Understanding big data analytics capabilities in supply chain management. Unravelling the issues, challenges and implications for practice. Transportation Research Part E: Logistics and Transportation Review, 114, pp. 416–436.

Backhaus, K., Erichson, B., Plinke, W. and Weiber, R., 2016. Multivariate Analysemethoden: Springer Gabler.

Cavicchi, B., 2018. You can't afford to be static: Rolling with the punches in forecasting. ABERDEEN, 2018. <https://www.ibm.com/blogs/business-analytics/aberdeen-reasons-adopt-rolling-forecasts/; https://www.ibm.com/downloads/cas/BRE7ALNK> [Accessed 13 May 2019].

Ceryno, P. S., Scavarda, L. F. and Klingebiel, K., 2014. Supply chain risk. Empirical research in the automotive industry. Journal of Risk Research, 18(9), pp. 1145–1164.

Chapman, P., Clinton, J., Kerber, R., Khabaza, T., Reinartz, T., Shearer, C. and Wirth, R., 2000. CRISP-DM 1.0. Step-by-step data mining guide. 2nd ed. [e-book]: CRISP-DM Consortium. <https://www.the-modeling-agency.com/crisp-dm.pdf> [Accessed 2 May 2019].

Christopher, M. and Peck, H., 2004. Building the resilient supply chain. The International Journal of Logistics Management, 15(2), pp. 1–14.

Czaja, L., 2009. Qualitätsfrühwarnsysteme für die Automobilindustrie: Gabler.

Fan, H., Li, G., Sun, H. and Cheng, T., 2017. An information processing perspective on supply chain risk management. Antecedents, mechanism, and consequences. International Journal of Production Economics, 185, pp. 63–75.

Gehr, F. and Hellingrath, B., 2006. Logistik in der Automobilindustrie. Berlin: Springer Verlag.

Geissbauer, R. and D'heur, M., 2010. 2010 - 2012: Global Supply Chain Trends. Are Our Supply Chains Able to Support the Recovery? Lessons Learned from the Global Recession. [e-book]: PRTM Management Consultans. <https://www.consultancy.nl/media/PRTM%20Supply%20Chain%20Trends%202010-2012-1019.pdf> [Accessed 13 May 2019].

Harland, C., Brenchley, R. and Walker, H., 2003. Risk in supply networks. Journal of Purchasing and Supply Management, 2003(9), pp. 51–62.

He, M., Ji, H., Wang, Q. and Ren, C., 2014. Big data fueled process management of supply risks: sensing, prediction, evaluation and mitigation. Proceedings of the 2014 Winter Simulation Conference, pp. 1005–1013.

Henke, M. and Besl, R., 2008. Supplier Risk Management in der Automobilindustrie. Risiken im Vorfeld erkennen, 2008(März). <https://beschaffung-aktuell.industrie.de/allgemein/risiken-im-vorfeld-erkennen/> [Accessed 25 April 2019].

Henke, M., Blome, C., Seifert, M., Grötsch, V. and Sauerbier, M., 2010. Intensives Risikomanagement oder flexibles Krisenmanagement? Überlebensstrategien im Automobileinkauf in der Wirtschaftskrise. Wiesbaden: EBS Business School, Supply Chain Management Instutitue (SMI).

Hevner, A. R., 2007. The three cycle view of design science resarch. Scandinavian Journal of Information Systems, 19(2), pp. 87–92.

Ho, W., Zheng, T., Yildiz, H. and Talluri, S., 2015. Supply chain risk management: a literature review. International Journal of Production Research, 53(16), pp. 5031–5069.

Hotz, I., 2007. Simulationsbasierte Frühwarnsysteme zur Unterstützung der operativen Produktionssteuerung und -planung in der Automobilindustrie. phd thesis. Magdeburg.

Khan, A., 2018. Managing risks under highly dependent supplier-producer relation in modern automotive industry. In: I. Dovbischuk, G. Siestrup, and A. Tuma, eds. 2018. Nachhaltige Impulse für Produktion und Logistikmanagement. Wiesbaden: Springer Gabler, pp. 141–152.

Kırılmaz, O. and Erol, S., 2017. A proactive approach to supply chain risk management. Shifting orders among suppliers to mitigate the supply side risks. Journal of Purchasing and Supply Management, 23(1), pp. 54–65.

Leveling, J., Edelbrock, M. and Otto, B., 2014. Big Data Analytics for Supply Chain Management. IEEE International Conference on Industrial Engineering and Engineering Management, pp. 918–922.

Lopez, E. and McKevitt, J., 2017. BMW halts production as Bosch fails to meet supply needs. 01.06.2017. SUPPLYCHAINDIVE, 2017. <https://www.supplychaindive.com/news/BMW-production-halt-Bosch-supplier-shortage-parts/443949/> [Accessed 11 May 2019].

Meierbeck, R., 2010. Strategisches Risikomanagement in der Beschaffung. Lohmar-Köln: Josef Eul Verlag.

Moder, M., 2008. Supply Frühwarnsysteme.

Nassif, A. B., Azzeh, M., Banitaan, S. and Neagu, D., 2016. Guest editorial: special issue on predictive analytics using machine learning. Neural Computing and Applications, 27(8), pp. 2153–2155. <https://doi.org/10.1007/s00521-016-2327-3>.

Oliveira, J. B., Jin, M., Lima, R. S., Kobza, J. E. and Montevechi, J., 2019. The role of simulation and optimization methods in supply chain risk management. Simulation Modelling Practice and Theory, 92, pp. 17–44.

Schlüter, F., Diedrich, K. and Güller, M., 2017. Analyzing the Impact of Digitalization on Supply Chain Risk Management. IPSERA Conference, Hungary.

Tang, O. and Musa, S. N., 2011. Identifying risk issues and research advancements in supply chain risk management. International Journal of Production Economics, 2011(133), pp. 25–34.

Thomé, A., Scavarda, L. F., Pires, S., Ceryno, P. S. and Klingebiel, K., 2014. A multitier study on supply chain flexibility in the automotive industry. International Journal of Production Economics, 2014(158), pp. 91–105.

Thun, J.-H. and Hoenig, D., 2011. An empirical analysis of supply chain risk management in the German automotive industry. International Journal of Production Economics, 2011(131), pp. 242–249.

Tiwari, S., Wee, H. M. and Daryanto, Y., 2018. Big data analytics in supply chain management between 2010 and 2016. Computers & Industrial Engineering, 115, pp. 319–330.

VDA, 2008. VDA 5009. Forecast-Qualitätskennzahl: Definition und Anwendung. Frankfurt: Verband der Automobilindustrie.

VDA, 2018. Automobilindustrie und Märkte, 2018. <https://www.vda.de/de/themen/automobilindustrie-und-maerkte.html> [Accessed 12 May 2019].

Volling, T., Matzke, A., Grunewald, M. and Spengler, T. S., 2013. Planning of capacities and orders in build-to-order automobile production. European Journal of Operational Research, 224(2), pp. 240–260.

Volling, T. and Spengler, T. S., 2011. Modeling and simulation of order-driven planning policies in build-to-order automobile production. International Journal of Production Economics, 131(1), pp. 183–193.

Wirth, R. and Hipp, J., 2000. CRISP-DM: Towards a standard process model for data mining. Proceedings of the Fourth International Conference on the Practical Application of Knowledge Discovery and Data Mining.