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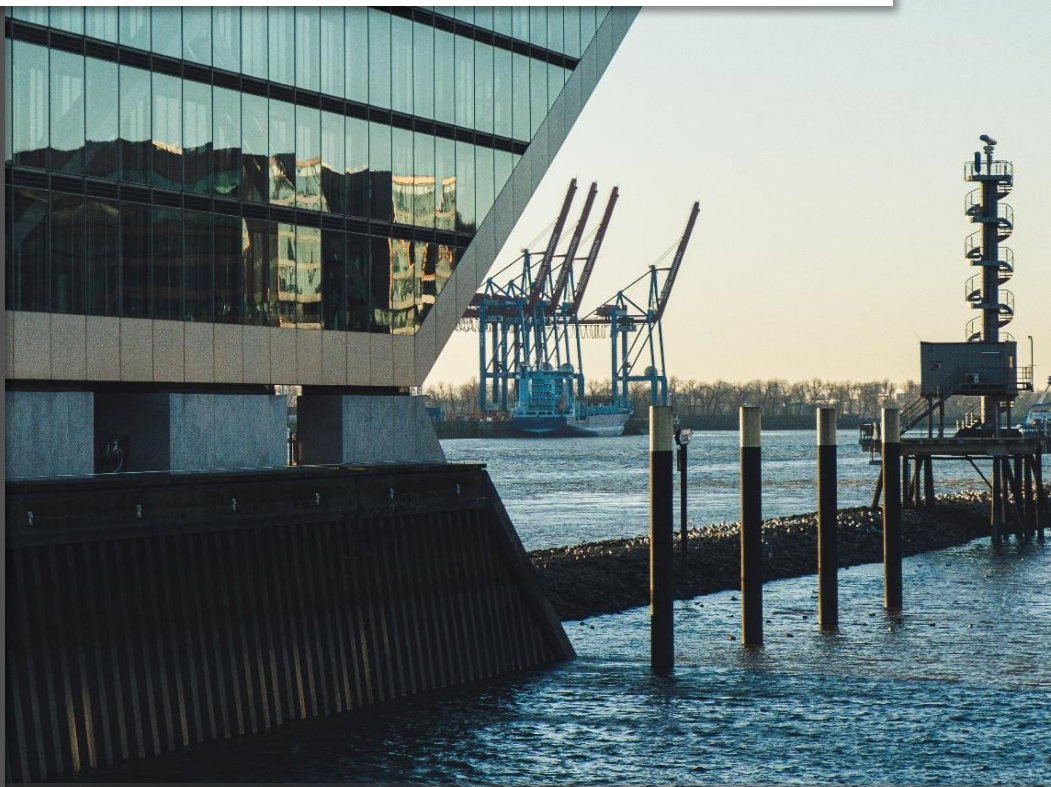

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A reference model for data-driven Sales Planning: Development of the model's framework and functionality

Daniel Büttner[1], Anne Antonia Scheidler[1] and Markus Rabe[1]

1 – TU Dortmund

Purpose: *Having accurate forecasts of future sales is mandatory for planning Supply Chains and providing the right distribution task resources. The usage of data in forecasting models enables precise planning and supports the company's competitiveness. This research shows a reference model framework that helps to establish data-driven sales planning in producing companies.*

Methodology: *The presented framework is derived from theoretical and practical challenges in a company where data-driven sales planning is not accomplished. The scope of the study originates from an industry project, and the developed framework forms the foundation for further research.*

Findings: *Data-driven sales planning is neither clearly defined nor the industry's norm, though data-driven methods exist for decades. The lack of methodical knowledge, incomplete data, and company characteristics cause diverse sales planning challenges. The research shows the requirements for integrating and advancing data-driven sales planning in companies.*

Originality: *This study clarifies the role of data-driven sales planning, identifies theoretical and practical challenges, derives requirements for the reference model and its functionality to support the establishment and advancement of data-driven sales planning in companies. The reference model aims for a comprehensive approach to counteract the mentioned challenges and guides the development of company-specific sales planning procedures.*

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1 Introduction

Flexible response of Supply Chains (SC) to the increasing volatility in the market (Mohamed-Iliasse, Loubna and Abdelaziz, 2020) has become a crucial factor for the company's success (Serdarasan, 2013), as customers determine the SC's success by purchasing products (Beckmann, 2012; Daugherty, Bolumole and Grawe, 2019). Frequently, the need for products originates spontaneously in the market, e.g., from the customers (Nimmy, Arjun and Pillai, 2019), usually met by the company's distribution system (Schulte, 2017). The relevance of distribution logistics for the overall economic success of a company (Daugherty, Bolumole and Grawe, 2019) is reinforced by the need for a shorter delivery time and the possibility of customers to substitute an unavailable product (Beckmann, 2012). Thus, company-wide planning must supply the distribution system with products to meet the customer's demand. In this context, it is necessary to anticipate market sales, because it enables the SC to provide resources in advance of the emerging demand (Magaña, Mansouri and Spiegler, 2017; Boone, et al., 2019). With the help of sales forecasts as a crucial part of the sales planning (SP) task, it is possible to have demand-oriented production and, thus, supply the distribution system (Chase, 2016). SP is a key task in the SC (Serdarasan, 2013) that is primarily company-specific (Aviv, 2001), as, e.g., it varies depending on the type of product sold. This research focuses on make-to-stock-producing companies that are capacity-constrained because they strongly depend on accurate sales forecasts (Nimmy, Arjun and Pillai, 2019). The company's dependence on consumption in the market makes data-driven SP particularly important, as products have to be manufactured in advance to the customer's demand. Data-driven SP uses the company's data and quantitative forecasting methods to estimate the future customers' product demand. SP is a SC-planning task, which provides information for other planning tasks, like distribution or production planning.

The forecast of future sales figures can be carried out through various methods (Kumar and Mahto, 2013; Rushton, Croucher and Baker, 2017). Quantitative methods are focused in the presented study, which can be beneficial to plan the SC accurately (Vogel, 2015). Big Data has emphasized data usage for planning the SC (Chokkalingam and Vijayarani,

2017; Ni, Xiao and Lim, 2020). Moreover, the increased availability and variety of data (Gantz, Reinsel and Rydning, 2018), especially for forecasting (Boone, et al., 2019), and higher computing power enable using sophisticated methods, like Machine Learning (ML), to predict future sales. Nevertheless, Chase (2016) cites a study that indicates insufficient use of existing data in the area of SP, even though the usage of historical data has already played a role since the introduction of time series methods, like exponential smoothing (R. G. Brown, 1959).

In order to improve the appropriate usage of data in SP and, thereby, the SC planning, a reference model (RM) is developed that details data-driven SP as a planning task in the SC. The model aims to support companies to select the right level of complexity regarding their data-driven SP. This research forms a basis for a data-driven sales planning reference model (SP RM) by providing its framework. A literature review is used to answer the following research questions (i) *What challenges exist in establishing data-driven SP?* The identified challenges are additionally confirmed through expert interviews at an industry partner. *The detected challenges are used to derive requirements for the SP RM. Moreover, the choice of reference modeling as an adequate modeling method is argued. This approach answers the second research question:* (ii) *What elements must a model incorporate to help address the identified challenges in SP in the practical application?*

For this purpose, the role of SP will be positioned in the Sales and Operation Process (S&OP) in Section 2. This includes the methods for and characteristics of data-driven SP. In Section 3, the methodical approach to identify challenges in SP and how the model will be further developed is shown. Section 4 presents challenges from the literature review. They are further compared with the expertise from the industry partner. In addition, the catalog of requirements and necessary functions of the data-driven SP is derived. Section 5 explains the aim and the framework of a data-driven SP RM. Finally, the findings are discussed, limitations are identified, and further research is pointed out.

2 Theoretical background for data-driven sales planning in Supply Chains

In this section, the role and importance of SP in SC planning and its effects on the SC are given. The definitions help to identify the research gap served by this paper.

2.1 Positioning of sales planning within the Supply Chain

Ayers and Odegaard (2018) define SC from a customer's perspective, which reflects this research's understanding of the term. The SC aims to provide the end customers with physical products or services, uniting multiple suppliers through flows of goods, information, finance, and knowledge. Schulte (2017) sees the customers' demand as the initiation of the SC and the Point-of-Sale (POS) data as the basis of managing the SC. Endogenous and exogenous trends lead to higher competitive pressure (Schiffer, et al., 2020). Therefore, accurate planning is necessary to react adequately to changes in the market. Frequent sales forecasts are needed, as using the most recent information provides more flexibility to the SC (Beckmann, 2012; Schiffer, et al., 2020). SP is one of the various planning tasks in a SC and obligatory, as it gives companies an estimate in which range the sales will be. Based on these plans, it is possible to prepare the SC system for the next period to reach a robust availability of goods to satisfy the customers' needs(Chase, 2016).

Before investigating SP, a distinction of the terms demand and sales must be carried out to narrow down the objective of data-driven SP. In economics, the term demand is defined by the quantity of a particular good or service purchased by economic entities with sufficient purchasing power (Meffert, et al., 2019). Therefore, demand, describes the fundamental need of customers to purchase products. Sales are understood as the number of products sold by a given company within a certain period (Gutenberg, 1984; Meffert, et al., 2019) thus, it has a more specific meaning than demand. The actual overall demand of the market will not be known, as the company's sales data would have to consider potential purchases in unexploited markets (Syntetos, et al., 2016). Mentzer and Moon (2005) refer to this term as independent demand originating from the end consumer. The term sales will be used in this paper, referring to this explanation.

SP is one part of the Sales and Operation Process (S&OP). The S&OP synchronizes demand and supply in a company (Thomé, et al., 2012) and starts with an estimate of the expected sales (Schulte, 2017; Lütke Entrup and Goetjes, 2019). Following various studies (Nimmy, Arjun and Pillai, 2019; Mohamed-Iliasse, Loubna and Abdelaziz, 2020; Iano, et al., 2021), SP is a crucial task in the SC, since it permits inventory and supply planning to determine production or distribution. The key element of SP is to develop an unbiased forecast of demand to have a data-oriented information function and not an action-oriented design function (Pieroth, 2013). The adjustments of sales plans through other business functions, e.g., due to restrictions of the SC system, are not part of SP (Usuga Cadavid, Lamouri and Grabot, 2018) as understood by this study. Figure 1 illustrates this deduction.

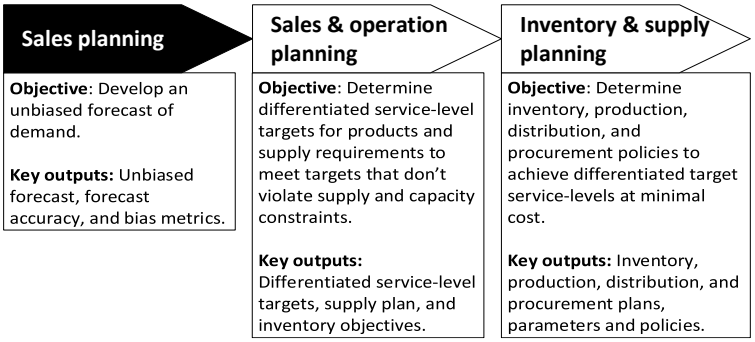

Figure 1: Delimitation of various Supply Chain planning tasks (according to Feigin, 2012)

SP can be conducted using numerous quantitative and qualitative methods. Figure 2 illustrates examples of some of these methods in the respective area. Qualitative methods are mostly subjective methods for assessing future development regarding the sales numbers, primarily verbal and rarely associated with numbers (Vogel, 2015). E.g., expert knowledge, brainstorming, or the Delphi method are used. This study focuses on using data from the IT landscapes in quantitative methods to provide objectivity of the SP to a possible extend.

Quantitative methods analyze empirical data with mathematical operations to derive a sales forecast (Vogel, 2015). The term data is often used as a conglomerate of the available contents of the information sources. The use of these data represents a necessary competitive factor for companies today (Ebener and Ebener, 2017). North (2011) states that the enrichment of data with meaning leads to information. It is impossible to delineate whether pure data sets or information exist in practice, as the designation of data attributes already goes beyond the data definition. As a basis for this paper, however, it can be stated that data are of great importance in data-driven SP. It makes use of primary quantitative forecasting methods to process numerical data using mathematical operations to obtain information about the market sales served by a specific company. 2

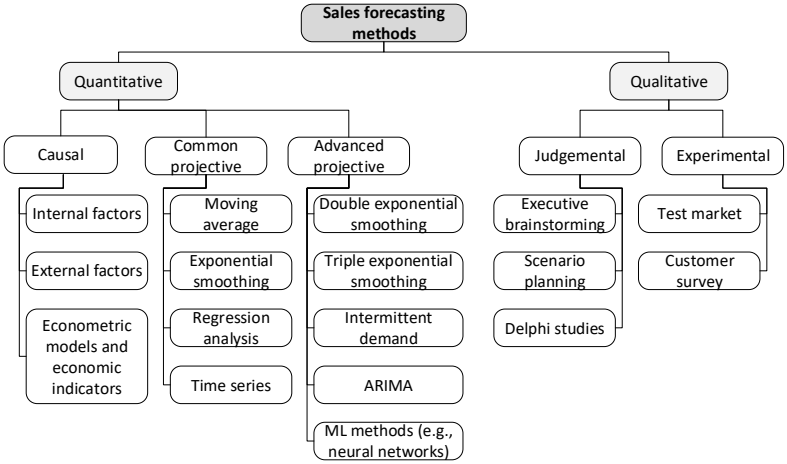

Figure 2 : Examples for quantitative and qualitative forecasting methods (according to Rushton, Croucher and Baker, 2017)

2.2 Reference modeling and deduction of the research gap

Reference modeling is used in numerous industry sectors (Fettke and Loos, 2004) to assist academics and practice. Some examples are business process engineering (Schwegmann, 1999), software engineering (Delfmann and Stein, 2007), or the design of production systems (Hartung, 2020). Schubel, Seel, and Schneider (2015) identify five topics in the logistics sector: Planning of logistics or production systems, SCM, digital factory, Computer Integrated Manufacturing (CIM), and Production Planning and Control (PPS).

A number of definitions (Scheer, 1998; Schütte, 1998; Schwegmann, 1999; Klinger and Wenzel, 2000; vom Brocke, 2002; Fettke, 2006; Fettke and Loos, 2007; 2009) exist, which do not provide a consistent understanding, as they come from different fields of expertise (Hartung, 2020). The major characteristics of the definitions identified above are presented to transfer the findings to the requirements catalog in Section 4.2.

- Recommendation character: RMs represent common practices or best practices for conducting business.
- General character: RMs are valid for a class of domains representing a simplified part of the reality and reducing diversity and complexity.
- Reusable character: RMs are conceptual frameworks that can be reused as a template for derived models.
- Modular character: RMs are modular and independent of the implementation software as they take on different perspectives.
- Clarity and uniformity character: RMs use a uniform and unambiguous language, for instance, to promote acceptance.

The RMs identified regarding the research object of this paper are: First, the Supply Chain Operations Reference Model (SCOR), which is an established RM (Beckmann, 2012) that aims to develop standardized processes to improve the exchange of information between companies in a SC. Uniform, comparable, and assessable processes are targeted, and best practice or software functionalities are shown (*SCOR,* 2010). In the model, demand planning and forecasting are defined and placed into the workflow. Possible tools, including spreadsheets and some forecasting methods, are discussed.

The level of detail is low, and, e.g., process steps to generate sales forecasts are not included (*SCOR,* 2010). Second, Continuous planning forecasting and replenishment (CPFR) is a framework to guide aspects of planning, forecasting, and replenishment processes through collaboration among the SC (VICS, 2002; 2004). The added value of the RM is based on the exchange of planning data instead of using sophisticated methods (VICS, 2002). SP is performed from the customer's side, as focused by this study. The task of demand planning is presented more concretely compared to the SCOR model. However, it remains generic and is presented in one process step called "create sales forecast" (VICS, 2002). In our opinion, this does not reflect the complexity of the SP task. Third, the RM of Gayialis (2013) uses knowledge modeling to optimize demand management and, thus, focuses on inventory and supply planning. Fourth, The business processes of SCs' for fruits are part of the RM of Verdouw et al. (2010). Processes are standardized to improve the creation of information systems and to increase the understanding of the management. There are few RMs for SC, especially for its sub-processes (Gayialis, et al., 2013). The study presented here addresses this gap, as the models mentioned above are not sufficiently precise concerning data-driven SP and focus on other or more general sub-areas.

3 Study's methodology

Three aspects regarding the methodological approach are explained here. First, a literature review was performed to identify the challenges in SP. Second, these challenges were checked and extended with a case study research to counteract them by defining requirements for the model. Finally, the methodical approach for developing the data-driven SP model is illustrated.

3.1 Methodology for challenges analysis

A literature review was performed to research the topic of data-driven SP and especially its challenges, mainly using Scopus (www.scopus.com), ScienceDirect (www.sciencedirect.com), and the catalog of the library of the Technical University Dortmund (www.ub.tu-dortmund.de). The review was conducted using the following

keywords in German and English language in different combinations: “data-driven”, “demand”, “forecast”, “reference model”, “sales”, “planning”, and “Supply Chain”. Approximately 200 sources were classified as relevant and reviewed, consisting of conference and journal papers, books, and surveys.

The research presented here is based on cooperation with an industrial partner, where data-driven SP was not established. Therefore, the challenges identified in the literature have been confirmed and extended with existing problems and challenges identified during the project time. The analysis of practical challenges for the SP task was performed with the help of a case study methodology. It is used to investigate a specific case in-depth and in a real-world context (Yin, 2014).

The cooperating industry partner is an international company that produces consumer goods, which are distributed through various external partners. The company aimed to advance the usage of data in the SC planning to raise customer satisfaction. Due to its great potential, SP was selected as the main area to advance. During the industry project, various methods were applied to improve data processing to generate adequate forecasts. Interviews were conducted with the management of different areas of the SC, such as planning, controlling, and operations, to understand the business model and, thereby, find factors that drive sales numbers. Furthermore, sales, customer service, operational logistics, IT departments, and various planning departments in different countries were interviewed to obtain comparable results. Data were gathered from multiple data sources, like the enterprise-resource-planning (ERP) or the customer-relationship-management (CRM) representing three markets to execute descriptive and prescriptive data analysis, e.g., Time-Series-Analysis. The research at the industry partner was used as an extension of the findings from the literature.

3.2 Methodology for a data-driven sales planning model

Reference modeling has been chosen for developing the data-driven SP RM. A corresponding procedure model complements the systematic approach to modeling and investigating the domain, explained here.

The RM is considered a modeling methodology in this research as it is helpful for theory and practice and can be used to strengthen an enterprise's market position (Fettke and Loos, 2007). The authors decided to use this method due to the following advantages, related to the sources in Section 2.2: Reference modeling aims to reduce effort to derivate a company-specific model. RMs moderate failure during the modeling process and improve the specified model's quality. The methodology further ensures transparency in a specific domain by consolidating knowledge and unifying the language. At the same time, RMs enable benchmarks and create a basis for comparing and assessing the current status quo.

Several procedure models for reference modeling have been found in the literature that show a large intersection. The approach of Akkasoglu (2014), following Schlagheck (2000), is chosen (Figure 3) since a feedback loop between the development and the application is integrated. Schubel, Seel, and Schneider (2015) criticize that it is unclear whether RMs are reused in practice. Therefore, the feedback from the cooperation partner has been used to increase the usability of the data-driven SP RM, thus, strengthen the practical relevance of the model.

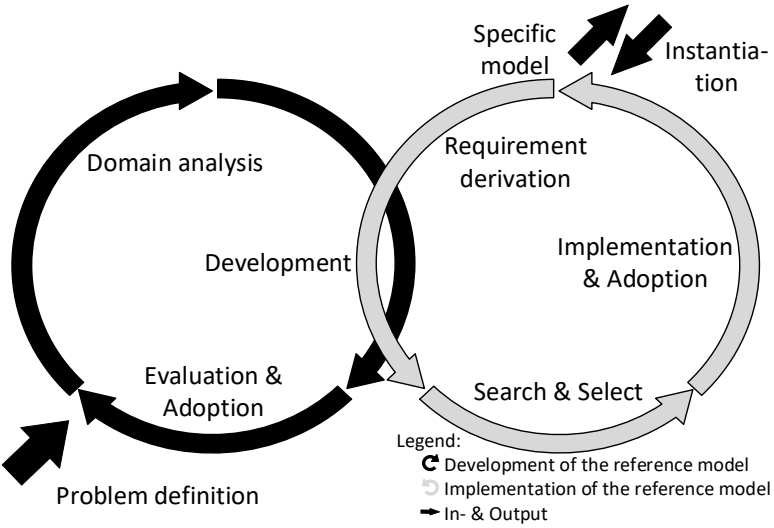

Figure 3: Procedure model for the development and implementation of reference models (according to Akkasoglu, 2014)

The procedure during the research is presented shortly according to the steps from the procedure model in Figure 3. During *problem definition*, practical challenges were analyzed in exchange with the project partner, and the research scope was defined. Afterward, a *domain analysis* in the form of a detailed literature review took place. Parallel to this, possible starting points were *searched and selected* in the company to achieve the target mentioned above. Continuous consultations with the partner and the results of the quantitative analyses helped to *implement* the data-driven SP in daily work. The company's characteristics were captured during *instantiation* with expert interviews, and the SP requirements in the company were derived. The *specific model* was realized in the form of a prototype that supports the data-driven SP. This prototype is a tool that processes the company's data within various quantitative forecasting methods. During the further *development*, the project experience derived a comprehensive model whose

validity can be transferred to other companies. *Evaluation and adaptation* are part of ongoing research activities.

4 Challenge analysis and requirements specification for the data-driven sales planning model

Challenges resulting from the literature review are presented and compared with practical problems, and required functions of the SP RM are presented to illustrate its benefits.

4.1 Challenges for data-driven sales planning

During the literature review, various challenges have been identified for the SP task, and grouped into three categories. The first challenge explores the "rising complexity in SC". The second challenge illustrates the heterogeneous characteristics of the "sales planning process". The third challenge is designated "rising complexity regarding information", describing data issues and the use of sophisticated methods, such as ML.

4.1.1 Rising complexity in Supply Chains

Rising complexity in SCs is a ubiquitous topic in many studies (Serdarasan, 2013; Schiffer, et al., 2020). Trends like globalization (Rushton, Croucher and Baker, 2017), digitalization (Ni, Xiao and Lim, 2020), and customer-centricity (Daugherty, Bolumole and Grawe, 2019) are mentioned. The volatility of markets is increasing (Mohamed-Iliasse, Loubna and Abdelaziz, 2020), which forces the industry to counteract with accurate planning to keep product availability high and balance the inventory (Sohrabpour, et al., 2021). The customers are a crucial factor for the SC (Nimmy, Arjun and Pillai, 2019) and conclusively for SP (Usuga Cadavid, Lamouri and Grabot, 2018; Iano, et al., 2021). The customers' expectations have risen significantly in recent years, and fast deliveries are now taken for granted (Daugherty, Bolumole and Grawe, 2019). Availability of goods is necessary in order to deliver them quickly, which in turn requires an accurate sales plan. Moreover, there is a tendency to sell products via various sales channels, e.g., simultaneously in

branches and through e-commerce (Syntetos, et al., 2016; Daugherty, Bolumole and Grawe, 2019), which is complicating SP, as more data sources can be considered in the forecast (Syntetos, et al., 2016). On the one hand, these developments make SP more complex (Tripp, 2019; Ni, Xiao and Lim, 2020) as markets become fragmented and dynamic. On the other hand, accurate SP can help operate the distribution system and raise customer satisfaction (Zhao, Ji and Feng, 2020).

4.1.2 Sales planning process

The forecasts of sales figures with data have a tremendous effect on the entire SC and have to be improved continuously (Nakano, 2009). SP is a multidisciplinary planning task (Beckmann, 2012; Riekhof and Brinkhoff, 2014) that can involve information from numerous departments, such as marketing and sales. According to various studies (Chase, 2016; Vereecke, et al., 2018), forecasting in practice has not advanced much regarding data usage and the planning process and still exhibits potential for improvement. Simple methods using historical sales data and expert forecasts are used frequently (Riekhof and Brinkhoff, 2014; Vereecke, et al., 2018), while forecasters in science tend to rather complex approaches (Green and Armstrong, 2015). SC sales forecasting is mainly conducted manually and based on the skills and knowledge of the data analyst (Seyedan and Mafakheri, 2020). Chase (2016), Syntetos et al. (2016), Seyedan and Mafakheri (2020), as well as Partida (2020) recognize that spreadsheets are still a common tool for the S&OP and the forecasting process. It appears that forecasting software tools are an issue to advance (Chase, 2016; Vereecke, et al., 2018), as these tools do not provide sufficient support for user-friendly presentation and processing of information across departments (Fildes, Goodwin and Önkal, 2019). SP takes place across departments, is complex and time-consuming (Seyedan and Mafakheri, 2020), requires many kinds of information, and, therefore, relies on the application of IT solutions (Mertens and Rässler, 2012). According to Syntetos, et al. (2016), there is a need for software solutions for SP, and its status is assumed immature (Alicke, Rachor and Seyfert, 2016). 3

The anticipation of sales is often confused or mixed up with financial, supply, or demand planning (Mentzer and Moon, 2005; Chase, 2016). Figure 3 illustrates the conflicting relationship between these four planning tasks.

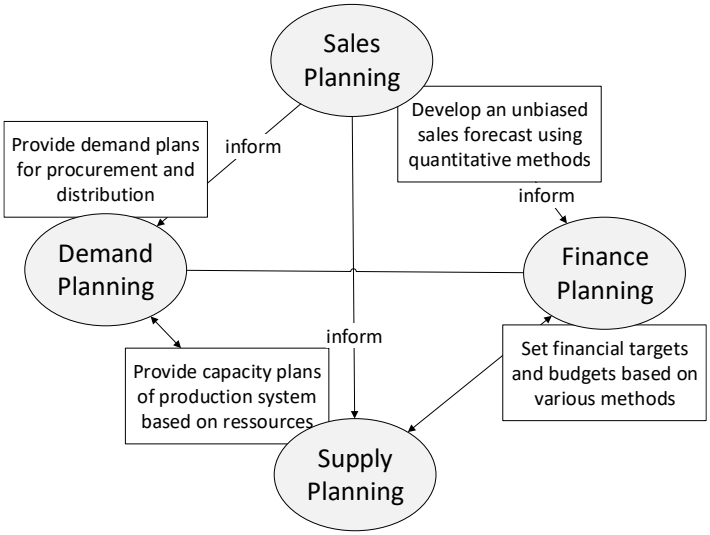

Figure 3 : Planning tasks and their objectives in Sales and Operation Planning (simplified illustration of respective tasks)

Finance planning is primarily a strategic task, defining goals for the following years, taking into account the respective business model. It is often influenced by a general desire for economic growth (Eilenberger, 2003). Resources limit supply planning, on the other hand. E.g., the focus lies on company-specific restrictions in the SC system, like production capacities (Lütke Entrup and Goetjes, 2019). SP and Demand planning are often used interchangeably. Referring to Mentzer and Moon (2005), it coordinates the dependent demand along the SC and, e.g., takes into account inventory and helps determine raw material requirements (*SCOR,* 2010). Misinterpretation of the tasks and synthesis of goals is a result of the vague delimitation of these business functions. Conclusively, the aim of data-driven SP is to create unbiased sales forecasts extrapolated

with quantitative methods using historical data from the IT landscapes to provide "objective" information in order to forecast the independent demand. These unbiased forecasts should not be confused with target setting or the operational execution, considering limited resources (Mentzer and Moon, 2005).

4.1.3 Rising complexity regarding information

Speaking of data-driven SP in times of Big Data and Artificial Intelligence being researched in many scientific areas, the role of data is of utmost importance (Camarinha-Matos, Afsarmanesh and Fornasiero, 2017). The amount of data recorded increases (Gantz, Reinsel and Rydning, 2018), and conclusively more data sources exist (Ebener and Ebener, 2017). This fact directly impacts the growth of databases in the associated IT landscape (Schiffer, et al., 2020). These data are becoming more important for accurate SC planning (Chase, 2016; Boone, et al., 2019). Knowledge should be extracted from data to understand which factors in the SC create sales peaks. Various sources note that data issues are critical (Beckmann, 2012; Camarinha-Matos, Afsarmanesh and Fornasiero, 2017; Schiffer, et al., 2020). E.g., Ni, Xiao, and Lim (2020) and Allen (2019) assume the lack of data as a fundamental problem in SCs. The survey of Vereecke et al. (2018) conveys a rather fundamental use of data and statistical forecasting methods for SP. One reason for this could be the low availability of data, their inadequate quality (Syntetos, et al., 2016; Makridakis, Spiliotis and Assimakopoulos, 2018), or missing knowledge in companies regarding data science (Hu, et al., 2018; Allen, 2019). The companies' databases are considered insufficient, leading Allen (2019) to see this lack of availability as an obstacle to the establishment of ML in practice. Data analysts spend 80 % of their time on data management (Chase, 2016). In order to achieve flexible SCs, automated and precise planning with sophisticated methods is necessary, which remains immature (Allen, 2019; Oosthuizen, et al., 2020). Creating sophisticated forecast models is time-consuming (Usuga Cadavid, Lamouri and Grabot, 2018) and challenging in SCM (Ni, Xiao and Lim, 2020). A SC is influenced by many factors, affecting the sales numbers (Serdarasan, 2013). These factors, such as sales promotions, must be integrated into the forecast models, while its recording and data representation are partially outstanding. Wenzel, Smit and Sardesia (2019) see potential usage for ML in SCM and various sources

(Mohamed-Iliasse, Loubna and Abdelaziz, 2020; Spiliotis, et al., 2020) concerning forecasting. Still, it has only been partially possible to use the data describing these factors to improve sales forecasting accuracy (Makridakis, Spiliotis and Assimakopoulos, 2018). More data and more complex procedures do not necessarily lead to more accurate forecasts (Green and Armstrong, 2015), as the effects of these factors cannot always be determined concretely (Spiliotis, et al., 2020). Furthermore, valuable data in an organization must be identified first (Chokkalingam and Vijayarani, 2017; Usuga Cadavid, Lamouri and Grabot, 2018). There was a contradiction in the scientific literature regarding the better suitability of simple (Green and Armstrong, 2015) versus sophisticated methods (Iano, et al., 2021) for forecasting (Spiliotis, et al., 2020). After years of gathering experience, the M4-Competition can state that both simple and sophisticated methods must be explored in the future, as the combination of these currently leads to the highest forecasting accuracy (Makridakis, Spiliotis and Assimakopoulos, 2020).

4.2 Catalog of requirements for the data-driven sales planning model

A frequently cited criticism relates to the varying scope and level of details of RMs (Fettke and Loos, 2007; Schubel, Seel and Schneider, 2015) and a missing evaluation method (Fettke and Loos, 2007). This criticism is met by creating a catalog of requirements before developing the RM for data-driven SP.

This catalog helps to develop the model correctly to counteract the challenges. It ensures formal correctness and focus during the model design. In this manner, it guides the development and helps to evaluate the model to meet theoretical and practical objectives and generate a remarkable benefit. Shortly explained, the requirement catalog determines what the model must be able to do and what has to be considered. The literature used in Section 2.2 regarding reference models was analyzed, and the claims for a RM were bundled. These general claims were synchronized with the identified challenges from Section 4.1 and transferred to the SP use case. The catalog was further expanded respecting the challenges in practice explained in Section 4.3. The requirement catalog for a data-driven SP RM and short descriptions are given in Table 1.

Table 1: Requirement catalog for the data-driven sales planning reference model

Requirement designation	Requirement description
Recommending	Aims to make recommendations to the model user, helping with implementation, execution, and extension of data-driven SP (considering common and best practices).
Generally valid	Creates a general overview in a domain (limiting itself to relevant aspects and clear applicability) by demonstrating relevant parts of reality and, thus, reduces complexity. Creates clear definitions and uses a unified terminology to create understanding and acceptance.
Reusable	Builds a conceptual framework using documented knowledge that serves as a template for deriving specific models in a particular domain.
Modular and expandable design	Software-independent; creates flexibility through its modular structure and, thus, enables dedicated model adjustment and expansion.
Aligned with standards	Systematical development of model and usage of appropriate and established methods (e.g., procedure model and modeling languages).
Consolidated methods	Merges existing quantitative forecasting methods and takes into account the respective application requirements.

Requirement designation	Requirement description
Positioning	Forms a reference value for the problem domain independent of the heterogeneous status quo and, thus, increases the comparability between companies (benchmark).

4.3 Comparison of the identified challenges with the company case

The project partner was supported in using its existing data as extensively as possible to create accurate sales plans. For this purpose, the SC was analyzed concerning its characteristics and customer requirements to identify sales-driving factors. The planning steps in S&OP and the respective use of methods were examined. The untapped potential was identified, and the usage of data in quantitative forecasting methods focused. There is considerable overlap between the challenges in the literature and those in the industrial project. Some of the challenges presented were more drastic at the practice partner than described by the literature. Some examples are given to illustrate this. The customer was one of the starting points for the research project with the industry partner. Its increasing requirements in terms of delivery times or sales channels were reflected in strong fluctuations in the sales figures. An increase in planning complexity due to serving many markets with different sales channels has also been confirmed by the experts. As described by the literature, spreadsheets were a frequently used tool at the start of the project, and simple forecasting methods or expert estimations were preferred. The mixing of planning objectives led to misleading communication and, thus, stockpiling of products that did not meet the demand. Furthermore, the use and storage of data still provides room for improvement, as the data structure and sources were distinctive. The simple and advanced forecasting methods produced acceptable results. Nevertheless, an improvement that is more remarkable was expected from sophisticated methods. The analysis of the case study through expert interviews resulted in the requirements "consolidation of methods" to help companies choose an appropriate

forecasting method and "positioning" to enable an assessment of the further development of SP. In summary, the authors assume that the lack of knowledge regarding quantitative methods and a missing awareness for the usage of data are reasons for a divergent maturity of SP, which strengthened the motivation for this research effort. However, adequate solutions in the literature to counteract these challenges do not seem to be sufficiently developed.

4.4 Determination of the functionality of the sales planning model

Due to various reasons, it can be stated that SP is a crucial and complex task, and its establishment is partly outstanding. The approaches in the industry are heterogeneous and diverse regarding the understanding of the SP task, the variety of forecasting methods, used data, and business procedures. Many producing companies create their sales forecasts based on pure domain knowledge or with the help of simple forecasting methods. At the same time, there is an urge for more precise planning. Referring to Riekhof and Brinkhoff (2014), 61 % of the companies surveyed produce forecasts based on historical data, while at the same time, 60 to 85 % would like to have a higher forecasting accuracy. This shows the rising importance of data usage in SP. SP is not clearly distinguished from other responsibilities in the S&OP, and planning objectives are confused. While data volumes and data sources are increasing, companies are not in the position to utilize them to improve competitiveness. It has further been shown that companies lack the expertise to use sophisticated methods. Based on experience, the authors claim that companies sometimes struggle to use simple forecasting methods. Accordingly, the authors assume that only a minority of companies make reasonable use of their data to predict future sales. It is obligatory to make the best possible use of the data available for SP and, thereby, support the success of the SC. The RM for data-driven SP, as presented in this study, promises to be of essential advantage for companies.

Figure 4 summarizes the challenges in SP on the left-hand side. The figure further shows the derived requirements for the SP RM. Before explaining the figure, functions for the SP RM are determined from the requirements. These counteract the challenges identified and, thereby, provide a frame for the resulting SP RM. The catalog of requirements

specifies a proper declaration of the SP RM functions. The functions of the model must meet the requirements to provide a benefit for practice and theory. How the SP RM framework considers implementing these functions is part of Section 5. In the following, some examples are given to illustrate the declared model functions. The rising complexity in the SC can be reduced as the model provides a template for companies to build specific SP solutions (*reusable*). The model helps to use data within a crucial planning task to support the overall efficiency of the value chain. Having a *generally valid* model with clear terms and definitions brings more transparency into the SP task. To counteract that forecasting has not advanced much in recent times, the model gives *recommendations* regarding reasonable complexity of the SP process and used forecasting methods. Companies can rely on the model independent of the used software and the level of their SP (*modular and expandable design*). The model allows the determination of the company's status quo regarding SP and shows possibilities for development (*positioning)*. The model is designed *expandable*. Thus, new forecasting methods can be added. A clear terminology and description of the SP task helps to prevent the mixing of planning objectives and promotes acceptance. The model is developed systematically. Existing knowledge is bundled and presented through adequate methods (*aligned with standards*). The model helps companies to identify forecasting methods eligible in their specific case and the data needed to predict future sales. *Recommendations* regarding the use of additional data and data sources in sophisticated forecasting methods need to be considered in the model. Levels of SP, e.g., from simple to advanced planning, have to be defined in the model to provide a benchmark (*positioning*) and comparability between companies.

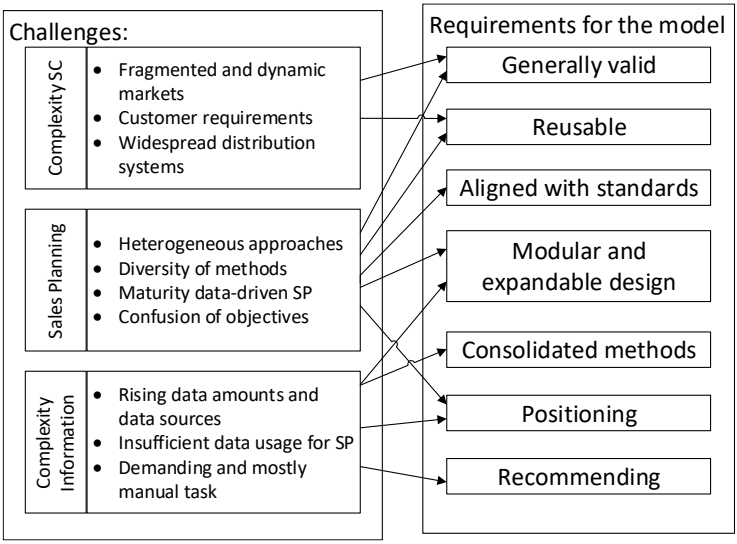

Figure 4: Identified challenges for data-driven sales planning and counteractive requirements for the reference model

5 Aim and framework of the data-driven sales planning reference model

In this section, the aim of the developed RM is presented to illustrate how the RM implements the requirement catalog. Subsequently, the RMs framework, the required levels in the model, and its functionality are evolved.

5.1 Aim of the data-driven sales planning reference model

The RM aims to counteract the mentioned tension (see Section 4). Based on this, a multi-level framework for the SP RM resulted, helping to design the SP task to reach an adequate forecasting performance. The model will illustrate the recommended quantitative methods for the SP process and the required information. The model

considers logistical and SP-relevant characteristics in the environment of producing companies. As the starting activity, the model's user parameterizes the RM. With the help of this parameterization, the functions that data-driven SP should provide are determined. Based on these functions, the model provides superior process sequences and concludes on relevant subordinate process steps. These subordinate process steps are further detailed in workflows to provide companies with detailed knowledge and guidance on data-driven SP. The model is supplemented by so-called information classes, which bundle corresponding data in defined categories. With these categories, the workflows of SP are brought into a context with the required information. Merging the functions of data-driven SP from the parametrization and the process steps with the assigned information classes generates detailed instructions for the planning task. The instructions can assist companies in designing their data-driven SP correctly. The data-driven SP RM will help to develop accurate sales plans and a transparent SP process. In addition, it will give advice for appropriate forecasting methods and the collection of valuable data. Furthermore, it gives orientation for the development of a forecasting model and helps as a benchmark, which shows a path for future orientation by defining levels of complexity regarding the SP task. The SP RM serves as an introduction to data-driven SP in the company and guides company-specific advancement regarding data-driven SP.

The data-driven SP RM could help companies to answer the following questions:

- How should existing data be used to predict future sales?
- How should the process of data-driven SP look like?
- What are the process steps to acquire a sales plan built with quantitative methods and starting with raw data?
- What is the current status quo regarding data-driven SP in the company, and how to advance this status?

5.2 The model's framework

The framework developed in this section demonstrates how the RM for data-driven SP can fulfill the requirements catalog and, thereby, derive benefits for practice and theory. The model levels are identified, and the functionality is shown to understand the

objective of each level and the transition between the levels. This study demonstrates the model's outer framework, and examples from the case study illustrate the inner model design, which needs to be detailed in further research. As an overview, the model's levels and short descriptions are shown in the following item list. In principle, a hierarchical top-down structure has been used that leads from coarse to fine. The terms in parentheses refer to the respective terms in Figure 5, which illustrates the model's framework in a simplified manner, indicated by "...":

7. Level **Instantiation:** The company's characteristics influencing the SP task are collected and used to instantiate the RM. Based on the parameters (P) that affect SP, the functions (F) needed in the company are determined to derive the proper process steps.
8. Level **Superior process**: In this level, fixed superior process sequences are defined. Each superior process sequence (1. Process sequence) has assigned process steps (1. Process step) that vary depending on the instantiation. The process steps are determined concerning the identified functions from the first level.
9. Level **Subordinate process**: The company-specific process steps from the level above are further detailed. Business Process Modelling and Notation (BPMN) is used as a modeling language to provide a step-by-step workflow to finish each process step and, thereby, superior process sequences.
10. Level **Information classes**: An information class bundles the data used in SP into defined categories. The Unified Modelling Language (UML) is used as a modeling language to attach data attributes to every information class. These Information classes are assigned to the workflows from level three.

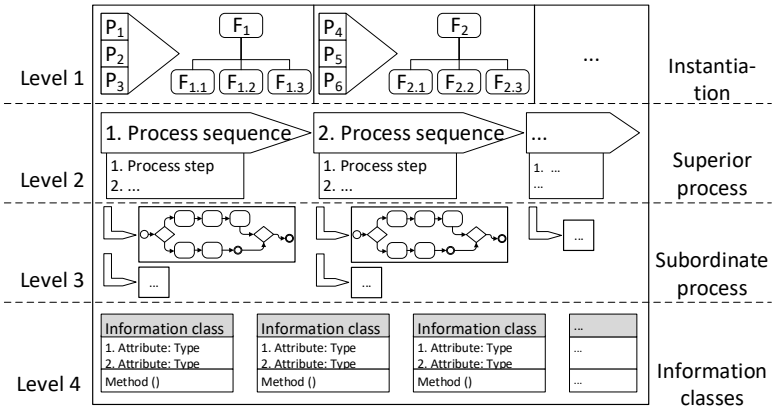

Figure 5: Exemplified framework of the data-driven sales planning reference model

The general framework has been designed in accordance with the catalog of requirements. The following methodical approach was chosen. Various possible actions were derived for each requirement in the catalog. The implementation of these actions in the RM was checked, and an adequate action was chosen. In this manner, the requirements have influenced the outer shape and the design of each level. All requirements not met within a model level are explained now. In the beginning, the topic was narrowed down to delimit the task of the model and, thus, obtain *general validity* for the model in the respective research topic. The model is intended to advise companies to introduce and continue data-driven SP, promoting the *recommending* requirement. Simultaneously, the model reduces complexity in the subject. It bundles knowledge and, thereby, provides a general orientation in this field. An instantiation level was created to adapt the general model to a concrete enterprise. Thereby, the model gives company-specific recommendations to improve the *reusability*. The requirement to *align with standards* is ensured using a procedure model that encourages a systematic development of the model. Furthermore, the *alignment to standards* is ensured by adapting existing modeling languages and using knowledge from state of the art, e.g.,

current forecasting methods. These forecasting *methods* are *consolidated* so that recommendations can be made for the usage of methods. The model forms a reference value for comparison of the complexity level obtained in companies, which is mainly determined by the forecasting method used. The reference helps to increase the comparability between companies (benchmark) and provides the *positioning* requirement. A *modular and expandable* structure is given since each level can be supplemented, and new levels can be created. Altogether, the SP RM promotes data usage for the SP task.

In the following, each of the model levels will be presented. Explanations are given regarding (i) the characteristics and main terms of each level, (ii) the requirements from the catalog that are met within the level, (iii) the input needed and the resulting output, (iv) the transition to the next level, and (v) the participants and target group. Finally, (vi) the methodical approach during the development is detailed, and (if used) the selected modeling language named, and (vii) an example of the inner model design is given.

5.2.1 Level 1: Instantiation

The instantiation level enables (i) the determination of the company-specific model. It adjusts the RM based on parameters, (ii) thus fulfilling the *recommending requirement.* (i) These parameters are used to determine which SP functions are needed in the company's use case. Therefore, (iii) the input to this level is the elaborated, company-specific parameters, and the required functions for the SP are the output. The determination of the SP functions (iv) takes place with the help of logical program sequences. Then, the identified SP functions subsequently determine which process steps are performed in Level 2. Domain experts are necessary for the parameterization (v), as they can use their business model knowledge to obtain an appropriate parameterization. Methodologically (vi), an extensive analysis in literature and workshops at the industry partner are conducted to identify the parameters that affect the SP task. A catalog of parameters is derived, and the relevant ones (affecting SP) are filtered and concretized. At the same time, all the functions that SP should fulfill are collected, categorized, and defined. (vii) For example, a company will define the following three parameters: (1) in which frequency data are collected, (2) in which

interval the planning should take place, and (3) over which horizon forecasts are created. The time intervals for creating forecasts designated as the "Iteration function" can then be defined with the help of these three parameters. This function is set to a weekly repetition, with each parameter's value, forecasting the next few weeks if data are collected adequately.

5.2.2 Level 2: Superior process

The superior process (i) defines the fixed process sequences needed to build data-driven sales forecasts. These sequences roughly represent the procedure for creating sales plans out of raw data. The process steps further detail each superior process sequence. Following this, the process steps are either necessary to be implemented or neglected, depending on the company situation. In this way, (ii) the model meets the *reusable* requirement and allows the derivation of specific models. (iii) The catalog of SP functions from Level 1 is used as input to define the necessary process steps for each process sequence. (iv) The identified process steps (for the company) can be further specified in the third level. The workflows in Level 3 are assigned to the process steps in this level. (v) The superior process level serves to inform involved entities in the S&OP how the forecasts are produced, meeting the (ii) *general validity* requirement, as it simplifies the complex task and raises understanding and acceptance of the involved entities. Methodologically (vi), various sources explaining the process steps of SP are considered. These sources will be bundled into a fixed process sequence and the assigned process steps. Correctness of this level is achieved through extensive scientific discussions with experts from IT, SC, and statistical research fields. (vii) The first process sequence, e.g., will be "Data gathering". If the instantiation shows that the available data only allow simple forecasting methods, process steps supposed to identify additional data sources are omitted.

5.2.3 Level 3: Subordinate process

The subordinate processes level (i) is more explicit than the process steps from Level 2. The workflows presented here give further detailed information on each process step. Concrete and systematic actions are defined for creating the forecast of sales (ii), meeting

the *generally valid* and *recommending* requirement. (iii) The identified process steps from Level 2 give the input, and the outputs are detailed workflows that specify concrete steps of actions in BPMN charts. (iv) A transition to the next level is unnecessary as the information classes are permanently assigned to the workflows in the BPMN charts. These workflows (v) primarily serve the responsible person to provide accurate forecasts and help him fulfilling his task. The workflows indicate the activities that can be automated through a suitable IT solution. (vi) The modeling language BPMN seems to satisfy (ii) the *align to standards* requirement, and the BPMN charts enable the definition of physical and computational processes. (vii) The workflow of the process step "data transformation", e.g., will clarify the preparations necessary to extract the sales numbers from the customer's order in the IT landscapes.

5.2.4 Level 4: Information classes

The information classes (i) help identify the company's suitable data to provide sales plans. (ii)The *reusability and general validity* requirements are met using generalized information classes. Data attributes are assigned to general information classes with adequate designations using plain text to circumvent the peculiarities regarding company-specific attribute designations. These classes provide a more common understanding for a set of enterprises. As an example, the identification keys in companies vary greatly, as some are sequential numbers, while others contain a date. It can be ensured that the model is helpful to various companies through bundling data with similar properties in information classes. (iii) The level's input consists of several information classes that reveal the necessary data in the SP. The output is the direct mapping of the information classes into the workflows from Level 3. (v) This level provides the information for the responsible person to produce the sales forecasts and helps IT departments prepare the technical infrastructure. (vi) UML is evident in expression and platform- and language-independent, thereby meeting (ii) the *align with standards* requirement. The *modular and expandable design* is given by the possibility to add or extend information classes. (vii) For instance, a central information class in this level will be the "order information", which contains, e.g., the identification key, the date

of purchase, and the ordered product quantity of the customers to extract the sales figures.

6 Conclusion

This paper presents the framework of a RM to help companies to implement and sustain data-driven SP. Challenges in SP were analyzed, and conclusions for the model were drawn to answer the first research question regarding the challenges for data-driven SP. The second research question focuses on the elements to be incorporated into the model. It is answered by first elaborating a definition of the term SP and second, by presenting the research gap as well as a reasonable modeling methodology. Furthermore, the research outlines a combination of difficulties identified in the practical domain and academic requirements into a model-specific requirements catalog. This catalog was further used to elaborate the objective and framework of the model. Each of the model's levels has been explained, and the methodical approach for development was presented. The model framework was applied exemplarily at the company, and its usefulness was confirmed in expert interviews.

The proper use of data for SC planning will be given greater priority in the future. SP forms a central element, which holds great potential due to new data sources and sophisticated forecasting methods. There is much knowledge in this field that needs to be bundled to make it more accessible to companies. Forecasting should have a more precise and distinct role in S&OP, as the use of data for sales forecasting is not yet fully established.

As a limitation, it should be mentioned that the presented framework has currently been developed only in reference to the case study and could be subject to further adaptations. The catalog of requirements must be further validated. It has to be proven to what extent the model can meet every respective requirement from the catalog. It is further necessary to validate the SP RM in additional companies.

According to the methodology presented here, the inner structure of the RM for data-driven SP needs to be further detailed to strengthen the model's general validity and increase the range of possible applications. The reasons for a relatively low

establishment of data-driven SP should be part of future investigations. A survey that clarifies the establishment of data-driven SP in the industry and the used methods is desirable. Overall, it appears that there are only a few generalizing models in the area of SP.

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