Value Driver Trees for KPI-Based Decision Analytics: Process Performance in the Order-to-Delivery Process

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Abstract

The order-to-delivery process is one of the most complex logistics processes. Knowing how to successfully satisfy customers through this process is a critical competitive factor for companies. However, there are no suitable methods for value-based decision-making in this process. One goal of this research is to systematically derive a value driver tree based on axiomatic design. Value driver trees are conceptual models that mathematically or logically explain the cause-and-effect relationships between value drivers and their key performance indicators. A systematic literature review and expert interviews in the German manufacturing industry were conducted to provide practitioners with a validated model. In addition, statistical certainty about the relationships between the drivers of the tree is required. A correlation analysis based on real-world case study data confirmed monotonic relationships between selected metrics extending decision analytics research.

Keywords: Value driver tree, order-to-delivery process, supply chain performance metrics, decision analytics, correlation analysis

1. Introduction

According to the well-founded (Estampe et al., 2013) supply chain operations reference (SCOR), the order-to-delivery process includes order and fulfillment activities (ASCM, 2023). This includes order creation, order preparation and conversion, goods assembly and shipping, and invoicing (Pfohl, 2022). This research focuses on the make-to-stock order-to-delivery process. As a core logistics process (Pfohl, 2022), it creates value for the company (Schnetzler et al., 2007).

Since value-based management seeks to maximize the value of the firm (Young & O'Byrne, 2001), it is necessary to manage this process in a customer-focused manner. According to Rappaport (1986), value can be understood as “shareholder value” (p. 13), which means maximizing the monetary value of a company from the perspective of its shareholders. Value drivers are causal-related financial or operational determinants that positively influence shareholder value (Wall & Greiling, 2011). Currently, there is no method for value-based management of the order-to-delivery process. However, value driver trees (VDTs) are a proven tool in the field of value-based management. VDTs are a systematic method for analytically and visually linking (operational) value drivers to strategic (financial) target indicators of a company (Koller et al., 2020). Although known for a long time, they are currently experiencing a rebirth due to the high availability of data (Gole & Shiralkar, 2020). Therefore, the objectives of this research are threefold. First, it is necessary to identify the benefits and limitations of VDTs for value-based management of the order-to-delivery process to understand how VDTs can be used. Second, there is a need to validate the value impact of this process on the value of a company. Third, it is crucial to empirically analyze how value drivers are related to each other to enable better decision-making.

This paper unfolds as follows: Section 2 provides a literature review to identify research gaps. The research methods are introduced in Section 3. These include a literature review and expert interviews, the modeling process, and correlation analysis in a case study. Findings on the benefits and limitations of VDTs, the model itself, and its empirical validation are presented in Section 4. Limitations (Section 5) and suggestions for further research (Section 6) conclude the paper.

2. Research background

2.1. Systematic literature review

The research gap must be demonstrated through a systematic literature analysis. The literature review process in this research follows the widely accepted approach of vom Brocke et al. (2009) to ensure rigor (Hevner et al., 2004) and relevance (Baker, 2000). It consists of five phases, as illustrated in Figure 1.

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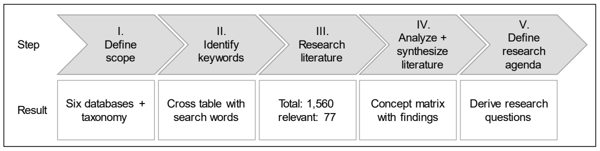

Figure 1. Process of literature analysis

To clearly define the scope of the research (phase I), the established taxonomy of Cooper (1988) is applied. The scope includes research findings and applications of value drivers and metrics in logistics. Six databases (Web of Science, Emerald, IEEE Xplore, ScienceDirect, ACM Digital Library, and WISO) were searched to conceptualize the findings. The reviewers collected and synthesized the literature to demonstrate the contribution of a particular point of view. The coverage is considered exhaustive and selective, aimed at general scholars and practitioners.

Key words were identified in terms of process and value (phase II). Each of those process key words (order-to-delivery, order-to-cash, order fulfillment, supply chain, value chain, logistics cost, distribution logistics) have been combined with value key words (value driver, result KPI, cost KPI, enabler KPI, value driver tree, Economic Value Added, EVA, driver tree, KPI tree, economic efficiency, economic viability, profitability analysis, metric).

Those were transferred to a combined keyword search of abstracts plus forward and backward search (phase III). By evaluating titles and abstracts, a total of 1,560 articles were analyzed[*], resulting in a relevant sample of 77 articles. This sample was collected according to the criteria of timeliness (from 2000 to current) and quality, considering articles published in scholarly journals and conference proceedings as these are mainly peer reviewed. Phase IV focuses on the analysis and synthesis of the literature using a concept matrix[*] based on Webster and Watson (2002). The included studies are heterogeneous in terms of related SCOR concepts and research methods. The findings are discussed in the following Section 2.2.

2.2. State of the field and research gap

Although a total of 16 studies developed VDTs to analyze supply chain performance, only Hahn and Kuhn (2012) and Schnetzler et al. (2007) tested their results in a real-world context. In addition, 13 studies focus on order management; 36 consider value orientation, and 12 discuss the interrelationship of metrics, but these aspects rarely occur together. Only six studies on order management either focus on value orientation (Lambert & Pohlen, 2001; Rahiminezhad Galankashi & Rafiei, 2022) or statistically test interrelations of metrics (Brabazon & MacCarthy, 2017; Nazari-Ghanbarloo, 2022; Sharma, 2021; Yildiz & Ahi, 2020). Beelaerts van Blokland et al. (2012), Hahn et al. (2021) and Zhang and Lam (2021) reconcile both aspects, but the supply chain reference is only at a high level of orchestration.

The identified articles do not provide a model for value-based analysis of process performance in the order-to-delivery process, nor do they empirically test whether there are interrelationships among key performance indicators (KPIs). This leads to the following research questions:

RQ1: What are the benefits and limitations of VDTs for value-based management of the order-to-delivery process?
RQ2: How is a VDT systematically derived for the order-to-delivery process?
RQ3: How can it be empirically validated that KPIs have a factual relationship to each other in the order-to-delivery process?

Those are addressed in research methods (Section 3) and research results (Section 4). They are structured in three subchapters each according to the research questions.

3. Research methods

3.1. Literature review and expert interviews

To answer the RQ1 regarding the benefits and limitations of VDTs for value-based management of the order-to-delivery process, the authors conducted a literature review and 16 semistructured expert interviews (Saunders et al., 2016). The interview partners were considered experts, mainly from medium and large German manufacturing companies in the business-to-business context. Three business process, five supply chain, and five management accounting experts have been interviewed. In addition, three interview partners from German universities completed the picture. The semistructured interviews included a prereviewed guideline[*] but also allowed for open responses (Saunders et al., 2016). The interviews were analyzed using qualitative content analysis[*] with inductive category application in two iterations for a systematic and replicable overview (Mayring, 2000). The findings of RQ1 can be found in Section 4.1.

3.2. Modeling process

Models are simplified representations of real events, objects, or processes that can describe relationships

[*] This document can be found at this link.

(Meredith, 1993). To determine how to systematically derive a VDT for the order-to-delivery process (RQ2), the proven model-building approach of Christensen and Carlile (2009) is followed (see Figure 2).

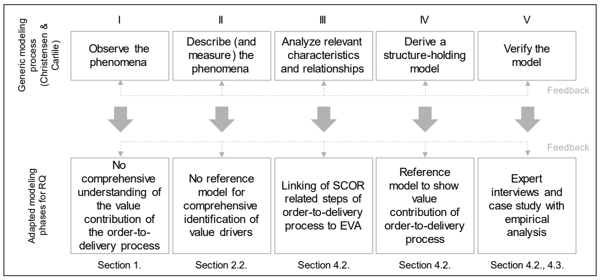

Figure 2. Modeling process

In this case, a lack of understanding of the value contribution of the order-to-delivery process can be observed (I). This is mainly due to the lack of a model for assessing the impact of the process on the value of a company (II). Therefore, the relevant SCOR elements of this process are linked to the value contribution of a company (III), which is summarized in a VDT (IV). Expert interviews were conducted to validate an extract of the model. A correlation analysis of the relationships supports the exemplary validation (V). The results of the modeling process can be found in Section 4.2.

3.3. Correlation analysis

To measure the impact of specific value drivers on EVA, supply chain metrics are needed to help evaluate performance so that it can be translated into value (Lambert & Pohlen, 2001). Because value drivers have causal relationships (Wall & Greiling, 2011), metrics that measure the performance of value drivers may also be interrelated. This section aims to determine how it can empirically be validated that KPIs have a factual relationship to each other in the order-to-delivery process. To answer RQ3, suitable KPIs are first derived from literature. Then, correlation analysis is applied.

Table 1. Overview of suitable metrics for FR-R

<table>
<tr><th>ID</th><th>Exemplary Metrics</th><th>Case Study</th></tr>
<tr><td>FR-11</td><td>Turnover</td><td>x</td></tr>
<tr><td>FR-A</td><td>Inventory turnover rate</td><td>(x)</td></tr>
<tr><td>FR-C</td><td>Order management cost</td><td></td></tr>
<tr><td>FR-Q</td><td>Return rate</td><td></td></tr>
<tr><td>FR-R</td><td>Perfect customer order fulfillment</td><td>x</td></tr>
<tr><td>FR-RO</td><td rowspan="3">Customer commit date achievement</td><td>x</td></tr>
<tr><td>FR-RW</td><td>x</td></tr>
<tr><td>FR-RT</td><td></td></tr>
<tr><td>FR-L</td><td>Lead time</td><td></td></tr>
<tr><td>FR-F</td><td>Delivery adaptability</td><td></td></tr>
</table>

According to ASCM (2023) and VDI (2002), the metrics in Table 1 below can be used to measure the specific value drivers of the decomposition of FR-Reliability that will be introduced in Section 4.2. The list of metrics is intended to provide a useful extract for further analysis. A full list can be found at the link[*]. For an overview of publications on supply chain performance metrics, see Mishra et al. (2018).

To determine how the KPIs are related, the theoretical propositions of the relationships (Section 4.2) were tested in a single real-world embedded case study (Yin, 2014). A large German manufacturing company in the business-to-consumer sector served as case study, and biased data from different organizational units were used. Selection criteria for the KPIs (see Table 1) were high data availability and comparable data structure. Hair et al. (2019) identified six steps for statistical evaluation. The steps are building the conceptual model (I), developing the analysis plan (II), evaluating the assumptions (III), estimating the model (IV), interpreting the data (V), and, finally, validating the model (VI). The results of correlation analysis can be found in Section 4.3.

4. Research results

4.1. Benefits and limitations

To answer RQ1, the findings from the literature review and the expert interviews are presented. According to Duda (2000) and Koller et al. (2020), the following benefits can be derived from VDTs. First, cause-and-effect relationships become clear. Second, it is possible to derive operational recommendations for action from the strategic goals since only relevant KPIs are considered. Third, improvement projects can be prioritized. Fourth, the model can be used as a communication tool to promote a common understanding of strategy and value drivers.

Through the expert interviews, the benefits mentioned in the literature were verified. In addition, the mathematical links in VDTs allow identifying potential correlations between variables.

VDTs also have limitations. First, all-encompassing trees become too complex (Koller et al., 2020; Schnetzler et al., 2007) but still need to have enough depth so that actions can be derived. Second, the model can be rigid, and necessary adjustments require a great deal of effort. Nevertheless, regular review is essential to avoid false accuracy (Koller et al., 2020). Third, identifying the most relevant value drivers is challenging when multiple stakeholders are involved. The use of mathematical relationships requires an assessment of how strong the influences of value drivers and KPIs are (Wall & Greiling, 2011). Fourth, different dimensions of quantitative and qualitative KPIs need to be reconciled (Schönsleben, 2023).

Again, the experts confirmed the disadvantages mentioned in the literature. In addition, they pointed out that the understanding of trees strongly depends on the perspective of the observer. Moreover, the implementation of VDTs in the corporate world is seen as a strategic decision to enable interdepartmental collaboration. The prioritization of KPIs and value drivers can still be ambitious, depending on the level of detail. Determining the mathematical robustness of such a model is also difficult. This means that the analysis of other data sets comes to the same results. This would require multiple, subsequent statistical testing of the model, with new data sets. Another disadvantage is that consistent use of VDTs is doubted in practice. Responsible persons would have to be determined for this. In addition, discussions about the method rather than the content are expected.

Considering the results, RQ1 can be answered as follows: The limitations and benefits found in the literature were confirmed by the experts. However, the interviews indicated that there could be many more limitations to the use of VDTs in the corporate world. Only two interviewees use such a tree in a business context. This indicates that the concept might be rather theoretical and is rarely used in the corporate world.

4.2. Decomposition of the order-to-delivery process using a value driver tree

RQ2 asks how a VDT is systematically derived for the order-to-delivery process. Therefore, the modeling process presented in Section 3.2. is applied. Since parts I and II are already considered in the previous sections, part III derives the value contribution of the order-to-delivery process. According to Lambert and Burduroglu (2000), measures of shareholder value are most appropriate for this purpose. Due to its high acceptance (e.g., Blendinger & Michalski, 2018) and intelligibility (Christopher & Ryals, 1999), the Economic Value Added (EVA) is considered the most suitable as a value peak ratio among the multitude of existing value-based metrics. EVA is a measure of economic profit that shows the difference between net operating profit after tax, also called NOPAT and the cost of capital. The latter depends on the total invested capital and weighted average cost of capital, known as WACC (Young & O'Byrne, 2001). EVA can be positively influenced by increasing sales, low capital costs of working capital and fixed assets, and low supply chain costs (Christopher & Ryals, 1999).

These financially oriented results of the value level are further broken down at the performance level into their (qualitative and quantitative) performance-oriented value drivers (Koller et al., 2020; Lambert & Pohlen, 2001). High logistics efficiency is achieved by high logistics performance on the one hand and low logistics costs on the other (VDI, 2002). These can be divided into the target areas of supply chain management: quality, delivery reliability, delivery lead time, flexibility, and costs (Schönsleben, 2023). The order of the target areas is determined by path dependencies, empirically proven by Ferdows and Meyer's (1990) sand cone model. This metaphor is used to illustrate a cumulative model for improvement, emphasizing the need to build a stable foundation of quality before addressing reliability, lead time, flexibility, and cost enhancements.

The subsequent enabler level considers the three main elements of the order-to-delivery process according to SCOR: order management, warehousing, and transportation. SCOR is a useful standard as it considers all decision levels (strategic, tactical, operational), all type of flows (physical, information and financial) and all levels of supply chain maturity (Estampe et al., 2013). Planning is excluded from the operational order fulfillment process. Order management includes receiving, entering, and validating the customer order, confirming inventory availability and delivery date, generating and submitting the order, scheduling transportation, notifying, confirming shipment, and processing payment. Warehousing encompasses receiving products from production or suppliers, picking, and packing. Transportation consist of loading the vehicle, creating shipping documents, shipping products, and providing proof of delivery (ASCM, 2023).

In part IV, a descriptive reference model is derived to visualize the value contribution of the order-to-delivery process. Based on the literature review and input from the expert interviews, six methods can be considered (process map, Ishikawa, cause-effect diagrams, failure mode and effect analysis, tree diagrams and supply chain design decomposition).

The goal of the model is to demonstrate the value impact of the order-to-delivery process on the value of the company and to show fundamental relationships. Therefore, the supply chain design decomposition based on axiomatic design was chosen for modelling. Key characteristics of axiomatic design (see Figure 3) are the basic distinction between functional requirements (what to achieve) and design parameters (how to achieve). Axiomatic design is based on two axioms. The independence axiom requires that functional requirements must be mutually exclusive. Each functional requirement carries one design parameter (1:1 relationship) that should be collectively exhaustive (Schnetzler et al., 2007).

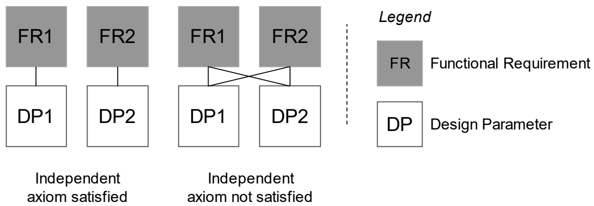

Figure 3. Examples for axiomatic design

The requirements of axiomatic design do not fully match the purpose of the model needed in this research. To verify a first draft of the model (V), the experts of the interviews (Section 3.1) additionally evaluated an extract of a VDT according to axiomatic design. The evaluation criteria were completeness, clarity, and consistency, as well as relevance and relationships of value drivers, among other things. While the excerpt was mainly considered to be complete, clear, and consistent, the experts criticized the 1:1 relationship between functional requirement and design parameter. Moreover, the independence of axioms was further not satisfied because the relationships between value drivers are complex and need to be visualized. Nevertheless, the omission of relationships cannot be supported as Ferdows and De Meyer (1990) empirically proved their existence in the sand cone model. Lastly, the experts missed a weighted and directed representation of the relationships. To overcome this criticism of axiomatic design, the model was modified. This means, first, that design parameters are no longer included in the model itself but are used to describe how certain functional requirements can be achieved. Second, the three levels (value, performance, and enabler level) are included, separating financial and operational value drivers. Third, relationships are displayed by dotted lines.

The results of the first evaluation (V) were used to further develop the model. Phases IV and V were consequently iterated through. Figure 4 represents the reviewed reference model (result of phase IV) showing the strategic decomposition of EVA in the order-to-delivery process. The general decomposition approach is based on Schnetzler et al. (2007). Basically, all elements are introduced in part III of the model-building process. The functional requirements (FR) are numbered consecutively, but for the sake of comprehensibility they are replaced by speaking keys.

The company's goal of achieving high EVA (FR-1) can be achieved by optimizing the value drivers in the order-to-delivery process. EVA is further decomposed according to the value target areas of the process. High sales revenue (FR-11) can increase value as well as low assets (FR-12 or FR-A), including low investment in current and fixed assets to lower cost of capital. Low cost (FR-13 = FR-C) means that decreasing operational cost can also increase EVA (FR-1).

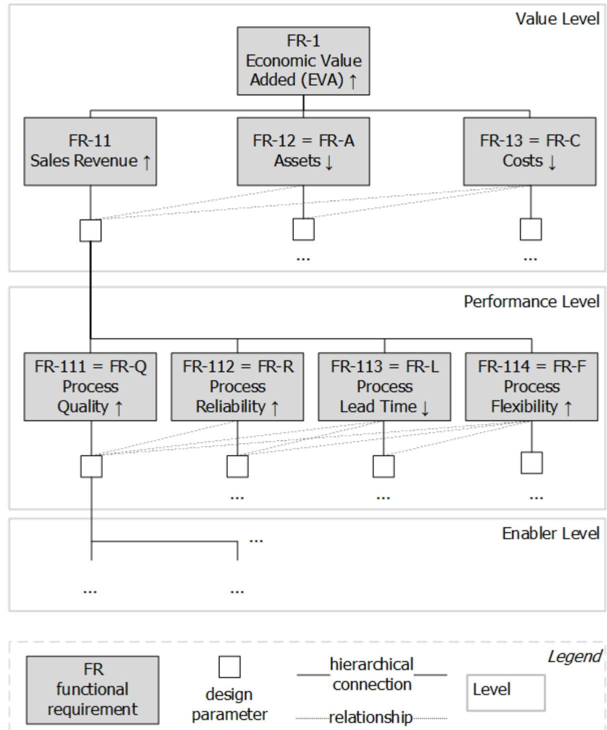

Figure 4. Strategic decomposition of the order-to-delivery process

To achieve high sales revenue (FR-11), customer satisfaction can be increased due to good order-to-delivery process performance when all customer requirements are perfectly met at the performance level. High performance can be achieved through four performance levels (Pfohl, 2023). High process quality (FR-Q) can be achieved when the customer's process requirements are met. This can include accuracy, consistency, competence, and safety (Schönsleben, 2023). High process reliability (FR-R) means performing tasks as required (ASCM, 2023); it ensures that the announced delivery date is met with a certain probability (Pfohl, 2022). Short process lead time (FR-L) measures the time between the start of a process and its completion (Sharma, 2021). The ability to adapt to new, different, or changing customer requirements, demonstrates process flexibility (FR-F) at a high level (Schönsleben, 2023). Together with FR-A and FR-C, these four areas form all the target areas according to the sand cone model. All six targets are further decomposed in the enabler level to the main elements of the order-to-delivery process (order management, warehousing, transportation). For better readability, verbal rather than numeric labels are used, for example FR-RO for high reliability in the order management. Due to high availability of data in the case study, the flexibility branch is explained in more detail (see Figure 5). The full tree can be found at the link*.

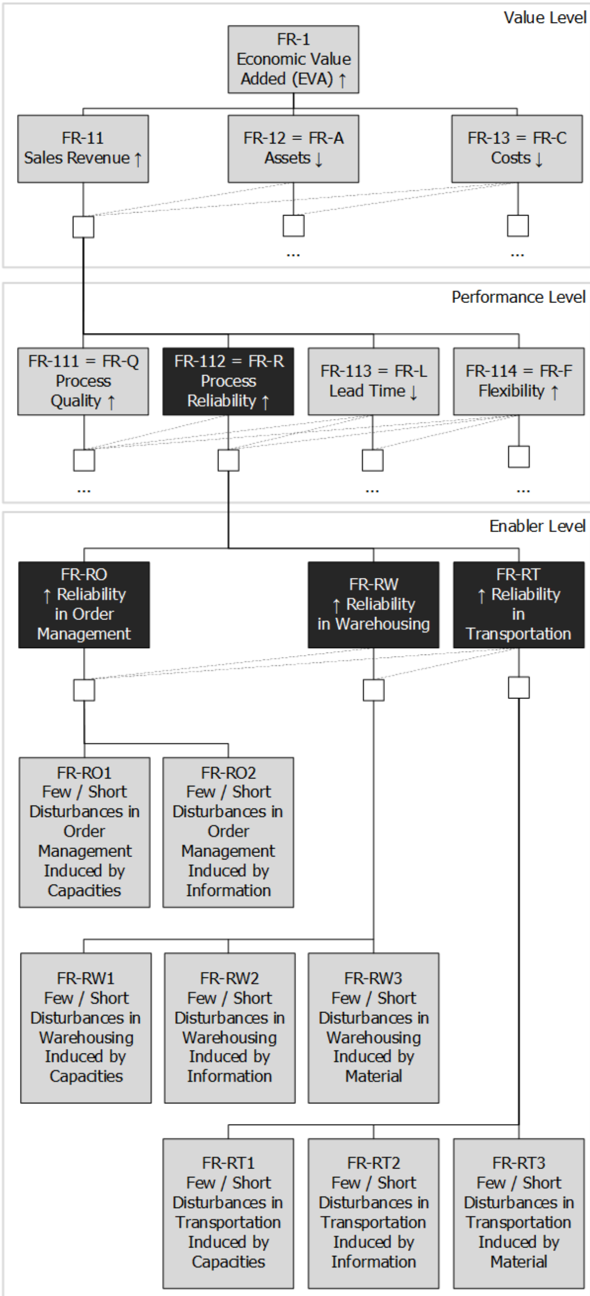

Figure 5. Decomposition of FR-R reliability

High reliability (FR-R) is achieved when cycle time variations are avoided. These variations can occur in order management (FR-RO), warehousing (FR-RW), and transportation (FR-RT). Variations in cycle times can be seen when delivery does not occur on the requested delivery date. Causes can be set rules in the process or unexpected incidents. Such disturbances must be corrected quickly by providing sufficient resources. These resources can be divided into capacities (e.g., employees, infrastructure, equipment), information (e.g., data for planning and control), and material (e.g., finished products) (Schnetzler et al., 2007).

High order management reliability (FR-RO) can be increased by reducing disruptions in order management or having short disruption times. A few disruptions in FR-RO due to capacity (FR-RO1) can be achieved, for example by an appropriate IT infrastructure. Short disturbances can be achieved with fast data access and trained staff to handle the problems. Few or short information-induced disturbances (FR-RO2) can be achieved, for example by high data quality and standardized processes. Material-induced disturbances do not make sense for order management, so this category is not included here. Accordingly, high reliability can be achieved in warehousing (FR-RW) and transportation (FR-RT). Taking FR-RW3 as an example, few or short material-induced disturbances in warehousing can be achieved by providing enough material at the right place at the right time.

Next to the hierarchical relationships, there are further cross-relationships at the value and performance level, represented by dotted lines. Due to the sand cone model, quality is a prerequisite for all other areas. Only when quality standards (FR-Q) in the order-to-delivery process are met through process standardization and high data quality (Sharma, 2021), can reliably delivery dates be announced to customers (FR-R). Only when process times vary little can processes be well accelerated and wasted time be eliminated (Sharma, 2021). This is done in lead time optimization (FR-L). High flexibility (FR-F) only benefits the customer if quality is assured, delivery dates are reliable, and lead times are generally short. Improving all these four areas can enable low assets (FR-A) and low operating costs (FR-C). Reducing inventory levels or cutting costs without considering the previous goal areas can result in decreased customer satisfaction and therefore lower sales. For example, reducing inventory (FR-A) without first improving reliability (FR-R) or lead time (FR-L) can result in out-of-stock situations. This ranking does not show which areas are most important. Rather, it sensitizes decision-makers to the direction of influence of individual value drivers. These relationships are shown as dotted lines (see Figure 4 and Figure 5). For example, if reliability increases due to higher reliability in the FR-RO1 using new IT infrastructure, more assets will be needed (FR-A), and operational costs could decrease due to fewer maintenance activities. Such relationships are represented by the dotted lines from FR-R to FR1, cross-connected to FR-A.

At the enabler level, there are also cross-relationships due to process flow. If reliability in order management (FR-RO) is not met, reliability in subsequent warehousing (FR-RW) and transportation (FR-RT) is even more difficult to manage. If promises are already made in the administrative phase, they can hardly be adjusted by warehousing or transportation.

With the model presented, RQ2 (How is a VDT systematically derived for the order-to-delivery process?) could be answered. For practical use, adaptions might be necessary (Koller et al., 2020). The next step is to validate the model. Part V was partially covered by the expert evaluation of the first model version. The empirical validation of these relationships is covered in the following section.

4.3. Monotonic relationships of KPIs

RQ3 addresses how can it be empirically validated that KPIs have a factual relationship to each other in the order-to-delivery process. Therefore, the process of statistical analysis (Section 3.3.) is applied.

Table 2. Selected metrics for FR-R

FR-11	**Customer order intake (COI)**
	Number of orders received, excluding cancelled orders
	Logistical sales (Sales)
	Number of sales from business towards end consumer measured by outbound deliveries
FR-A	**Inventory level (Inv)**
	Average amount of stock in units
FR-R	**On time delivery (OTD)**
	1 – Ratio of delayed order lines and total order lines Delayed: 1st confirmed goods issue date < actual goods issue date
FR-RO	**Planning and order management performance (PLP)**
	1 – Ratio of delayed order lines and total order lines Delayed: 1st confirmed goods issue date < last confirmed goods issue date
FR-RW	**Warehouse performance (WHP)**
	1 – Ratio of delayed order lines and total order lines Delayed: last confirmed goods issue date < actual goods issue date

The VDT (Section 4.2) can be used as a conceptual model (I). The analysis plan (II) shows the development of certain metrics from January 2021 to mid-May 2023. To ensure a sufficient sample size, data were analyzed on a weekly basis, including a sample size of 375 cases. The metrics in Table 2 were selected to measure the impact of the value drivers. Distribution costs (FR-C) could be evaluated on a monthly basis only and are therefore at too high a level of aggregation. Return rate (FR-Q), customer commitment date achievement in transportation (FR-RT), lead time (FR-L), and delivery adaptability (FR-F) could not be measured and were therefore excluded. Data analysis was performed using the statistics software SPSS version 27.

All KPIs used are on a metric scale. The rate of missing data was 11.7%, which is slightly higher than the recommended 10% (Hair et al., 2019). In fact, this was accepted as it regularly constituted different metrics for different cases not allowing imputation techniques. However, missing data can lead to increased variability, loss of information and ultimately reduced significance. All outliers were accepted in order to interpret the data in terms of their true distribution. Correlation analysis was chosen as appropriate technique. It identifies the strength and direction of relationships (Backhaus et al., 2021). For example, Yildiz and Ahi (2020) used it to determine the interdependence of SCOR performance metrics.

The prerequisites for Pearson *r* correlation analysis (III) are metric scale, no extreme outliers, linearity, and bivariate normal distribution (Ofungwu, 2014). In this case, metric scale is fulfilled, and outliers are accepted. Linearity can be checked graphically by a scatterplot with LOESS line, and histograms show the distribution of variables (Hair et al., 2019) (see Figure 6).

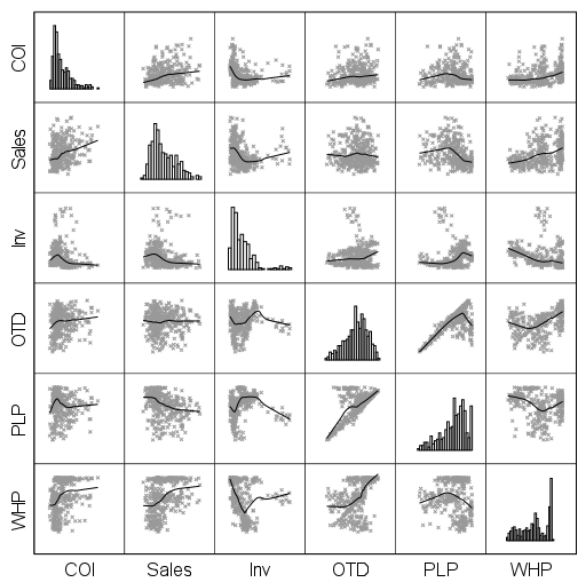

Figure 6. Correlation matrix with histograms

The LOESS creates a smooth line in the scatterplots to identify the nature of relationships (Ofungwu, 2014). For linearity, there must be a strong organization of points along a straight line (Hair et al., 2019). Therefore, linearity cannot be detected. The histograms indicate that none of the variables meet the requirements for normal distribution. An additional Kolmogorov-Smirnov test confirmed this assessment. Since the conditions for Pearson *r* are not met, Spearman's Rho (ρ) could be used. It detects monotonic relationships by ranking data rather than using the actual data. Therefore, the prerequisites of normality and no outliers do not need to be met (Ofungwu, 2014).

To estimate the model (IV), the range of values of ρ is normalized from -1 to +1 and can measure the degree of monotonic relationships. Dependent and independent variables are not distinguished, so cause-and-effect relationships cannot be indicated. Measures with $\rho \geq 0.7$ are considered strong correlations, and $\rho \leq 0.3$ are considered weak correlations (Backhaus et al., 2021). The power of the test is determined by the actual correlation. The significance level is generally accepted to be $p \leq 0.05$ (Hair et al., 2019). The following hypotheses can be introduced:

H_0: $\rho_{xy} = 0$ $\quad\quad$ H_1: $\rho_{xy} \neq 0$

H0 indicates that there is no monotonic correlation between variables *x* and *y*. H1 indicates there is a monotonic correlation. The variables *x* and *y* are placeholders for each of the six variables used: COI, sales, avg. inv., OTD, PLP, and WHP. All correlations ρ can be seen in Table 3. Correlation is only valid if underlying relationships are monotonic (see Figure 6).

To test the significance of the detected correlations (VI), the *p*-value can be used (Backhaus et al., 2021). This is included in Table 3. With a significance of $p<0.01$, the null hypothesis that there is no monotonic correlation between sales and COI can be rejected. A positive correlation of $\rho=0.268$ is considered weak. Increasing sales correlate with increasing COI and vice versa. This relationship has already been shown in Figure 6. If the significance is $p>0.05$, the null hypothesis cannot be rejected. For example, the null hypothesis that sales and OTD are not monotonically correlated cannot be rejected.

This section has shown that correlation analysis can be a partial way to provide empirical evidence of relationships between sporadic KPIs. Only monotonic correlations could be identified. This means that neither statements about other correlations (e.g., linear or cubic) nor about causality can be made. A big learning here is that data quality as well as availability affect the quality of the analysis. RQ3 could be partially answered. Further analysis of cause-and-effect of relationships in regression analysis could not be conducted: The first two of the four prerequisites linearity, normality, heteroscedasticity, and absence of correlated errors (Hair et al., 2019) are not met. Data transformation could cure the violated prerequisites, but this should be avoided if an explanation of the data is required, as in this case (Hair et al., 2019).

Table 3. Spearman's Rho correlation

			COI	Sales	Inv	OTD	PLP	WHP
Spearman's ρ	COI	Correlation Coefficient	1.000					
		Sig. (2-tailed)						
		n	375					
	Sales	Correlation Coefficient	.268**	1.000				
		Sig. (2-tailed)	0.000					
		n	363	363				
	Inv	Correlation Coefficient	-.329**	-.354**	1.000			
		Sig. (2-tailed)	0.000	0.000				
		n	375	363	375			
	OTD	Correlation Coefficient	.130*	0.010	0.085	1.000		
		Sig. (2-tailed)	0.015	0.852	0.110			
		n	352	341	352	352		
	PLP	Correlation Coefficient	-0.103	-.393**	.375**	.502**	1.000	
		Sig. (2-tailed)	0.053	0.000	0.000	0.000		
		n	352	341	352	352	352	
	WHP	Correlation Coefficient	.357**	.405**	-.387**	.489**	-.131*	1.000
		Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.014	
		n	352	341	352	352	352	352

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

5. Limitations

There are limitations to all three methods used. It depended on human judgment to determine which literature was considered important in the systematic literature review. Human judgment also played a role in the interviews. Semistructured interviews are not standardized by nature, so replicability is not fully guaranteed. The bias of the interviewer and the interviewee also play an important role. Due to the small sample size, the results cannot be generalized. Although the interview guide and the systematic method of Mayring's content analysis were used, full validity cannot be guaranteed. Regarding the VDT, the modification of the axiomatic design needs further evaluation by experts and practical validation, also in full extent. The data in the case study were available only as biased data from selected organizational units of the case company for a limited period of time. Therefore, the analysis performed indicated monotonic correlations for this specific case. Because the conditions for regression analysis were not met, causal relationships could not be established. The correlation could only be shown by example, as not all of the necessary data was available.

6. Conclusion and future research

The objectives of this research were threefold. RQ1 (What are the benefits and limitations of VDTs for value-based management of the order-to-delivery process?) was answered through a literature review and expert interviews. Key benefits are clear cause-and-effect relationships, linking strategic and operational goals for better decision-making, and transparency. The main limitations are complexity, mathematical robustness, and rigidity. A modification of axiomatic design could be a useful method to systematically derive a VDT for the order-to-delivery process. This was shown by an excerpt from the reliability branch. RQ2 (How is a VDT systematically derived for the order-to-delivery process?) could thus be answered. Correlation analysis can help to show how the value drivers of a VDT are related to each other. RQ3 (How can it be empirically validated that KPIs have a factual relationship to each other in the order-to-delivery process?) could be partially answered. Data quality and availability have a major impact on the quality of the analysis. Correlation analysis confirmed the existence of monotonic relationships between selected metrics in this process. The latter is thus a first indication that the model built in the context of RQ2 is functional and should therefore be used in further research.

The limitations of the research are directly related to the potentials for future research. For VDTs, research could be conducted on how to represent mathematical relationships of qualitative and quantitative metrics. Regression and factor analysis can be used with different data sets to determine causality. Multi-criteria decision-making techniques or simulation can help determine the importance of value drivers.

Overall, this study contributes in two ways: It extends the research on decision analytics by statistically testing the correlations of key indicators for analyzing process performance, and it provides practitioners with a validated process model for deriving company-specific VDTs, enabling them to make better decisions.

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