

Sebastian Lodemann, and Wolfgang Kersten

Supply Chain Analytics Implementation – A TOE Perspective



CC-BY-SA4.0

Published in: Adapting to the Future:
Wolfgang Kersten, Christian M. Ringle and Thorsten Blecker (Eds.)
ISBN 978-3-754927-70-0, September 2021, epubli

Supply Chain Analytics Implementation – A TOE Perspective

Sebastian Lodemann¹ and Wolfgang Kersten¹

1 – Hamburg University of Technology

Purpose: *Increasing quantity and sources of data and their potential to fuel value-adding applications in Supply Chain Management (SCM) are of considerable importance for corporations.*

Methodology: *We utilize a qualitative research design of semi-structured expert interviews.*

Findings: *Utilizing the Technology-Organization-Environment framework, we establish an integrated perspective: We propose that CSF possess a varying relevance to the success of the SCA (Supply Chain Analytics) project, depending on the initial drivers.*

Originality: *While the benefit and potential value of SCA is established, the implementation of the technology remains a challenge for companies. This paper combines the concept of “drivers” for adoption with Critical Success Factors (CSF) during the initial implementation.*

First received: 11. Apr 2021

Revised: 29. Aug 2021

Accepted: 31. Aug 2021

Supply Chain Analytics Implementation

1 Introduction

Improving business processes based on data analytics is a major opportunity for companies to establish competitive advantages aside from classic productivity advantages or arduous and risky product innovations (Davenport, 2006). While this might sound like an old hat, the developments in data availability as well as the amount and properties of these data, indicate a new paradigm in analytics potential (McAfee, et al., 2012). Moreover, increasing data-driven decision making is associated with higher productivity as well as market capitalization (Brynjolfsson, Hitt and Kim, 2011).

However, despite the promises, a third of data analytics initiatives within companies do not live up to their expectations (NewVantagePartners, Bean and Davenport, 2018). Our findings suggest that this is in part due to a narrow consideration of relevant Critical Success Factors (CSF) on the part of companies – a more holistic perspective seems necessary. Additionally, generating a close fit between the drivers for adoption and the project to be implemented is useful. To do that we develop a categorization of drivers. Our focus are the initial stages of a Data Analytics (DA) project within the Supply Chain Management (SCM) function, i.e. a Supply Chain Analytics (SCA) project. These are often stated as Initiation, Adoption, and Implementation (Kwon and Zmud, 1987; Matta, Koonce and Jeyaraj, 2012). Arising issues during the operational phases of SCA are not the focus of our study. We consider SCA to be a technological concept, i.e., a driver of change related to the digital transformation in SCM (Kersten, et al., 2017) that is enabled by a set of underlying technologies and processes.

To provide a holistic view perspective, the Technology Organization Environment model (TOE, Depietro, Wiarda and Fleischer, 1990) is an established framework to approach technology implementation. It also has established roots within a diverse set of SCM adoption considerations (e.g. Lin, Lee and Lin; Chan and Chong, 2013) It is one model among many, with one primary differentiating factor regarding models in the same realm such as Diffusion of Innovation (DOI, Rogers, 2003) or Technology Acceptance Model (TAM, Davis, 1989) being its dedicated inclusion of environmental factors (Oliveira & Martins 2011, p. 119). This is crucial for our area of investigation, as SCM by its nature

relates to up- and downstream processes and thus considerations in the environment of the focal company.

The current paper aims to present a comprehensive perspective on reasons for a lackluster track record of SCA projects and provides recommendations for potential improvements on the path ahead.

To do that, we formulate the following research questions:

RQ1: “What are the primary CSF for successful implementation of SCA?”

RQ2: “Are different CSF varying in importance when considering the drivers for the respective SCA initiative?”

The paper is structured as follows. In section 2, a brief introduction into theoretical background is provided, establishing term disambiguation of the utilized phrases and determining the relevance of the topic at hand. Hereafter, Section 3 establishes our methodological approach, and provides the results of our preliminary, quantitative study, motivating the main study. We then present the qualitative interview study in chapter 4, diving deeper into CSF and drivers for SCA before providing a conclusion in Section 5.

2 Theoretical Background

2.1 Supply Chain Analytics

Data Analytics remains an evolving field with ambiguous definitions and connections to adjacent domains (Gröger, 2018). To clarify, we briefly outline our understanding of the term: SCA comprises numerous techniques with varying levels of sophistication (Alahakoon and Yu, 2013). It goes beyond purely descriptive approaches and aims to inform future decisions through data-driven analysis and exploration of relevant business problems.

Though in practice, many applications are based on Big Data, there is some progress to achieve value-adding outputs via the use of smaller data sets (using approaches such as Transfer Learning, cf. e.g. (Gao and Mosalam, 2018) and (Zhou, 2016) or Virtual Sample

Supply Chain Analytics Implementation

Generation, cf. (Wanigasekara, et al.). Due to that fact, we prefer the term Advanced Analytics. We follow the broad definition “*Advanced [data] analytics is defined as the scientific process of transforming data into insight for making better decisions.*” (Rozados and Tjahjono, 2014, p. 1100). We understand SCA broadly as “[...] *“the use of analytical tools and approaches in supply chain environment in order to make more informed decisions and ultimately improve supply chain performance.”* (Zhu, et al., 2018, p. 48), thus encompassing all three major categories of Data Analytics; Descriptive, Predictive and Prescriptive Analytics. These are used to generate a better understanding of a field, build improved decisions on that understanding and by doing so “establish[] competitive advantages” (Wamba, et al., 2015, p. 235). In that endeavor, the underlying methods naturally include state-of-the-art techniques such as machine learning that are commonly attributed to the field of Artificial Intelligence.

Various researchers have brought forward the important overlap of data analytics with supply chain management (Waller and Fawcett, 2013). The universal increase in data volume is remarkable and naturally translates into the realm of logistics and supply chain management: Over 1.6 billion new data items are generated by a logistics network every month (Ilie-Zudor, et al., 2015). These increasing amounts of data are generated by more and more diverse sources. Unstructured data, that is difficult to analyze with traditional approaches, make up an increasing share (Raman, et al., 2018).

Besides increasing data, tools do deal with that data are also emerging both on the software side (e.g. frameworks such as Tensorflow or PyTorch that make it easier to implement analyses instead of building from the ground up (Lu, et al., 2018)) and on the hardware side (e.g. GPU and TPU to faster execute calculations for neural nets, the essential tool in machine learning (Fernandez Molanes, et al., 2018)).

With both more data and the means to generate value from these data, it is thus clear that SCA is a crucial capability for corporations today. In fact, “[...] [Big Data Analytics Capability] is a significant predictor of [Firm Performance].” (Akter, et al., 2016, p. 124). By enabling faster and more accurate decision-making, Analytics can be seen as “the only sustainable competitive advantage” (Cokins, 2013, p. 69), since all of Porter’s (Michael, 1985) traditional strategic approaches are potentially eroded due to technological and market-based developments (Cokins, 2013).

2.2 Information Technology Implementation

Existing models considering the implementation of information technologies (IT) possess varying degrees of complexity, with different phases, as introduced e.g. in (2010, phases Agenda setting, Matching, Refining, Restructuring, Clarifying, Routinization) or (1987, phases Initiation, Adoption, Adaptation, Acceptance, Routinization, Infusion).

On a basic level, however, comparable models can be boiled down to three higher-order stages: Pre-adoption, Adoption und Post-adoption (Damanpour and Schneider, 2006; Kamal, 2006). These three macroscopic stages are conceptionally congruent with Lewin's (1947) 3-Stage Model of Change (Matta, Koonce and Jeyaraj, 2012). In the first stage, *unfreeze*, the organization is being prepared for a change. Correspondingly, this is where the initiation of the technology implementation takes place. The particular relevance of a "cognitive element" in this initial phase was already described by (Pierce and Delbecq, 1977). The awareness of a possibility for change or the pressure towards such a change can thus be seen as the individual perception of a decision-maker. This is where our study is positioned and the focus of our expert interviews lies: What are the drivers for this initial decision to adopt SCA and what are the CSF for successful implementation. We elaborate in section IV.

Theories considering the adoption of IT can be differentiated according to their focal entity: Either they focus on the individual or incorporate an organizational perspective (Fichman, 1992). Primary theories and models with an individual focus are the Technology Acceptance Model (TAM, Davis, 1989), the Theory of Planned Behavior (TPB, Ajzen, 1985; 1991), and the Unified Theory of Acceptance and Use of Technology (UTAUT, Venkatesh, et al., 2003) with the extension UTAUT2 (Venkatesh, Thong and Xu, 2012).

Theories with an organizational orientation include Diffusion of Innovation (DOI, Rogers, 2003) and Technology-Organization-Environment (TOE, Depietro, Wiarda and Fleischer, 1990). For TOE, Technology considers the factors that have technical connotations, Organization looks at the features and attributes of the organization and Environment is concerned with the surroundings in which the activities of the company occur (Bhattacharya and Wamba, 2018).

Supply Chain Analytics Implementation

The different theories and models have corresponding focal areas and thus attract proponents and opponents. E.g. (2011) prefer the TOE framework, due to an inclusion of an environmental facet, which bears considerable implications for technological implementations. We use TOE as well in this paper, as it has been shown to match empirical results from IT adoption studies (Thong, 1999) and provides the holistic perspective our interview study has shown as beneficial.

3 Methodology

We utilize a qualitative research design of semi-structured expert interviews.

In a previous study to establish the relevance of our approach, we surveyed German SCM professionals, resulting in 104 partial and 86 complete records. The experts were recruited through the network of the Federal Logistics Association in Germany. We found a large discrepancy between the perceived relevance and the degree of implementation regarding the application of SCA (see Fig. 1). Based on this finding we conclude an apparent need for SCA in the companies. Due to the lacking nature of implementation efforts (as described in the introduction) we focus our research on SCA implementation to enhance SCA usage in general.

For our main study, we conducted 24 in-depth expert interviews to better understand the reasons for the discrepancy we found. The interviewees are based in Germany (though often in international corporations), our analysis is thus limited to a German context at this point. Our sample comprises the fields Plan, Source, and Deliver according to the Supply Chain Operations Reference Model (SCOR) classification. We exclude production-related functions. This was done to focus our study on the primary relevant use-cases, as the SCM-task *Production* accounts for only 7 % of research considerations of AI in SCM and Logistics (Hellingrath and Lechtenberg, 2019). We exclude the *Return* function as well, as there is a limited number of use cases at this point.

Since the aim of this paper is the theory-guided analysis of considerations like SCF and drivers for implementation, we use *purposeful sampling* (Patton, 2002). Patton differentiates a diverse set of specific approaches, this paper utilizes *criterion sampling*

combined with *purposeful random sampling*. The main criterion in the former sampling method is the occupation of the interviewees: The experts questioned operate at the intersection of supply chain management and data analytics and thus can provide domain application knowledge regarding the supply chain while simultaneously being familiar with technological, implementation, and application challenges regarding the SCA field. Our experts work in multiple industries but, due to their SCM focus, often face similar hurdles and opportunities in their business. The interviewees include both managerial as well as operative roles. The *purposeful random* nature of our sampling is expressed through the absence of prior knowledge regarding the success of the respective SCA initiative, thus reducing a selection bias.

Table 1: Interviewees for qualitative study

#	Position	Sector
1	Director Operations Analytics	Maritime operations
2	Product Owner BI	Consumer goods
3	Senior Analytics Consultant	Consulting
4	Data Analytics Specialist	Medical technology
5	Head of Software Development	Manufacturing industries
6	Artificial Intelligence Consultant	Consulting
7	Data Scientist	Electronics industry
8	Head of Data Ontology	Maritime operations
9	Lead Data Scientist	Information & Communications Technologies

Supply Chain Analytics Implementation

#	Position	Sector
10	Manager Artificial Intelligence	Information & Communications Technologies
11	Executive Analytics Manager	Consumer goods
12	Manager Logistics	Consumer goods
13	Manager Logistics	Manufacturing industries
14	Project Manager	Logistics Provider
15	Director	Logistics Provider
16	Project Business Partner	Aviation
17	Supply Chain Manager	Consumer goods
18	Distribution Planner	Luxury goods
19	Production Planner	Manufacturing industries
20	Head of Supply Chain Management	E-Commerce
21	Chief Collaboration Officer	Logistics Startup
22	Purchasing Specialist	Medical technology
23	Manager Procurement	Manufacturing industries
24	Manager CoE Data Analytics	Aviation

The semi-structured interviews were based on a questionnaire that was employed to structure the interview, with the option to dive deeper in topics that were not anticipated. This generated a compromise between comparability on the one hand and new insights and paths for future research on the other. The interviews were conducted in person and on the phone, then transcribed and coded as a qualitative content analysis. Since we aimed to find evidence for CSF and drivers we previously discovered in existing literature, but also remain open for new factors, we employed a combined system of a deductive and inductive course of action. Specifically, initial macroscopic categories were defined based on theory, sub-categories then emerged based on the interviews (Schreier, 2014).

The main research questions are stated as:

- RQ1: “What are the primary CSF for successful implementation of SCA?”
- RQ2: “Are different CSF varying in importance when considering the drivers for the respective SCA initiative?”

Supply Chain Analytics Implementation

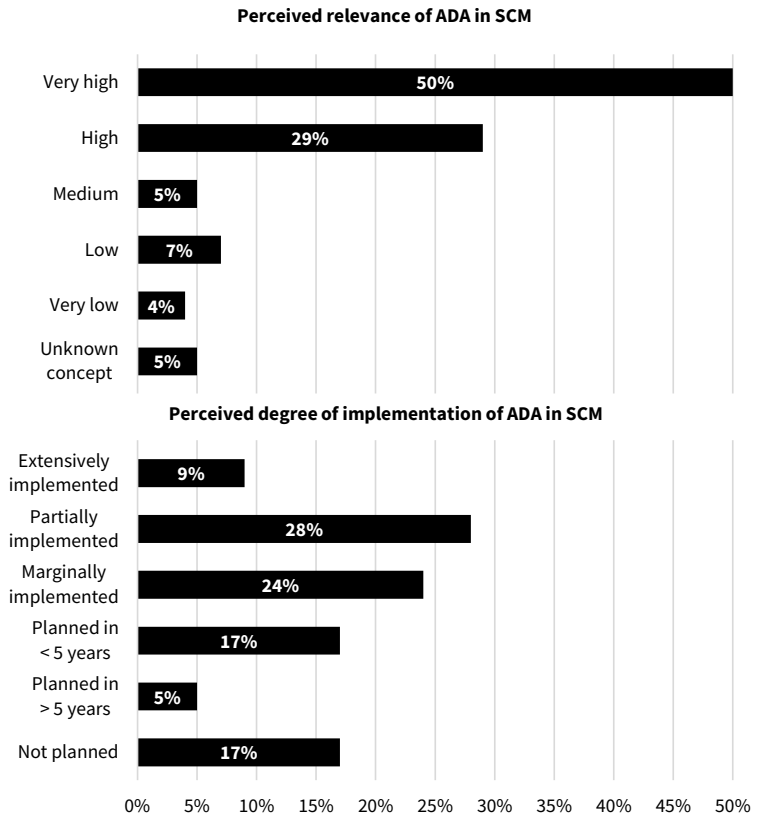


Figure 1: Perceived relevance and degree of implementation of Advanced Data Analytics in Supply Chain Management for respondents' own company (Lodemann and Kersten, 2020)

The question was stated as “Advanced Analytics in Supply Chain Management”, which we reframed as SCA in this paper

4 SCA Implementation: CSF and Drivers

4.1 Critical Success Factors

Literature identifies a broad collection of facilitators and hurdles regarding successful IT implementation. The aim of defining CSF is to identify parameters that have a distinct effect on the success of an initiative (Haenecke, 2002). Critics have questioned the approach, e.g. stating that CSF are too simplistic to objectively represent reality and invite bias (Boynton and Zmud, 1984). Proponents of the approach counter that CSF help to identify the core, overarching factors that can subsequently be substantiated, and provide an initial top-down perspective where to focus ones attention (Boynton and Zmud, 1984), thus generating an easier path towards acceptance of senior management (Müller and Jugdev, 2012). We follow this argument and seek to attenuate the critique by focusing the CSF we identified to our narrow field of SCA and emphasizing their guiding, rather than all-encompassing, nature. CSF are regularly used regarding our field of investigation (e.g. (Gao, Koronios and Selle, 2015; Denolf, et al., 2018)).

The CSF are presented according to a TOE-differentiation. This emphasizes the holistic nature of the approach: Our evidence indicates that, as literature suggests, simply focusing on a purely technological approach does not suffice for overall success.

Table I does not claim to represent all CSF of data-driven endeavors but rather considers the most relevant ones for the particular case of SCA. We list those CSF that were identified by multiple experts and provide sources to show that these are also taken into account by literature. Not all literature sources are concerned with the focus on SCM, some just deal with SCA applications from a more general perspective. In this case, the CSF was mentioned by our experts but has not yet been discussed in SCM-related literature. To build a picture as complete as possible, more general sources were used to provide literature-based support for these CSF. Since we aim to provide the view of practitioners here, CSF that are proposed by literature but were not mentioned by our experts are omitted in Table I. Large collections of CSF for IT can be found in e.g. (Hameed, Counsell and Swift, 2012).

Supply Chain Analytics Implementation

Table 2: CSF for Successful SCA Implementation

CSF	Source
Technology	
Data quality	(Lamba and Singh, 2018),(Kwon, Lee and Shin, 2014),(Moktadir, et al., 2019),(Wang, et al., 2016),(Wuest, et al., 2016)
Data security	(Lamba and Singh, 2018),(Moktadir, et al., 2019),(Richey, et al., 2016)
Data availability	(Wang, et al., 2016),(Wuest, et al., 2016),(Sanders, 2016)
Data variety / Data complexity	(Moktadir, et al., 2019)
Storage of (currently unused) data	(Richey, et al., 2016)
Technical Infrastructure	(Wamba, et al., 2015),(Wang, et al., 2016)
Organization	
Support/Involvement of Top Management	(Wamba, et al., 2015),(Lamba and Singh, 2018),(Schoenherr and Speier-Pero, 2015b),(Queiroz and Telles, 2018),(Wang, et al., 2016)
Selection of appropriate method	(Lamba and Singh, 2018),(Wang, et al., 2016),(Wuest, et al., 2016)

CSF	Source
Adequate resources	(Lamba and Singh, 2018),(Wang, et al., 2016)
Identification of relevant and appropriate use case	(Sanders, 2016),(Schoenherr and Speier-Pero, 2015b)
Data-driven focus of corporate culture	(Queiroz and Telles, 2018),(Wang, et al., 2016),(Sanders, 2016)
Integration into existing processes	(Schoenherr and Speier-Pero, 2015b)
Employee qualification	(Lamba and Singh, 2018),(Moktadir, et al., 2019),(Schoenherr and Speier-Pero, 2015b),(Queiroz and Telles, 2018),(Richey, et al., 2016),(Wang, et al., 2016),(Sanders, 2016)
Existence of product champions	(Bhattacharya and Wamba, 2018)
Structured change management approach during implementation	(Schoenherr and Speier-Pero, 2015a)
Time constraints / Time management	(Moktadir, et al., 2019)
Consideration of privacy issues	(Schoenherr and Speier-Pero, 2015a)
Environment	

Supply Chain Analytics Implementation

CSF	Source
Cross-company cooperation	(Queiroz and Telles, 2018),(Kache and Seuring, 2017)
Up- and downstream integration of information systems	(Lamba and Singh, 2018),(Richey, et al., 2016)(Brinch, 2018b),(Brinch, 2018a)
Consideration of regulatory actors	(Nam, Lee and Lee, 2019)
Partner transparency	(Richey, et al., 2016),(Shen and Chan, 2017)
Development of technological standards	(Bhattacharya and Wamba, 2018)

4.2 Drivers for implementing SCA

The initial impetus to an SCA project can have diverse causes. We call these causes “drivers”. Different terms are used in theory as well as by our experts, e.g. “motivation”, “impulse”, “aim”, “reason” or “trigger”. Literature describes drivers for different information technologies across varying fields, however, the topic of drivers for SCA is scarcely researched.

The unifying characteristic for the different terms is the ex-ante nature of the driver, meaning that we look at the situation and observed drivers *prior* to adoption. Different benefits or side-goals often emerge during implementation, which are not in our focus. The drivers can be endogenous, originating from within the organization or even an individual decision-maker's perspective or exogenous, (as (Alles, 2015) uses the term) resulting from outside of the direct scope of the focal corporation.

Table 3: Categories of Drivers for SCA

Abbreviation	TOE classification	Categories of drivers for SCA
Endogenous types		
DA	T	Use available data to add value
TI	T	Apply new technological possibilities to build up competencies and communicate this internally
SI	O	Solve a specific (operational) issue
TR	O	Increase transparency/understanding in a particular area of business
Exogenous types		
TE	T	Apply new technological possibilities to communicate this externally
CO	E	Draw level with competitors who already use SCA
PA	E	Fulfill a demand by partners and customers

All drivers in Table II are assigned an abbreviation to refer to them more concisely here, as well as their primary relevant category according to the TOE framework. However: the different drivers can contain diverse nuances according to other areas: Driver SI can, for instance, contain technological elements, such as a difficult manual data collection task

Supply Chain Analytics Implementation

that is easier executed employing a Natural Language Processing (NLP)-based data mining approach.

We try to underline this fact by the additional split in endogenous and exogenous types. While driver TE is classified as exogenous (and thus could be naturally considered an environmentally focused driver), our experts see the *initial impetus* as technological: Applying SCA as a technology, with the *subsequent benefit* of using this in external communications, such as employer branding or marketing initiatives, emphasizing the technological prowess of the company.

5 Discussion

5.1 CSF

One CSF that is not discussed by literature but was emphasized by the experts is “interdepartmental cooperation”, meaning the intra-organizational exchange of information and ideally diverse setup of teams made up of different divisions.

We find that no expert considers all CSF that are proposed by literature. This is not surprising when taking into account the vast number of CSF that have been discussed in the past. More troubling to us is another finding emerging from this: Most experts are concerned with CSF that are more closely related to their background, i.e. practitioners with a technologically focused role (e.g. data scientist, data engineer) have Technology-CSF in mind, while others with more business (e.g. Supply Chain planners, Process Owners) or managerial roles – who are of course also involved in SCA projects – have the OE dimensions as their focal points. This is to be expected: One considers the domain with which one is familiar. The primary issue regarding CSF thus seems to be the unidimensional focus, rather than a general ignorance of relevant CSF.

When considering previous implementation difficulties, it became particularly evident that the consideration of a more diverse set of CSF would have supported the SCA effort. Most often, the focus is on technological CSF. We deduce from this finding, that companies are advised to focus on diverse teams that bring varying backgrounds, and hence perspectives, to the table. Additionally, “cross-qualifying” employees would be

beneficial: Educating a manager with deep knowledge of the business-related issues regarding technological challenges enables a more holistic perspective. In this spirit, (Landing AI, 2018) proposes a gradational approach for AI qualification: Broad, introductory courses for only weakly related functions or top-management and more concrete skills-building for tightly involved personnel.

5.2 Drivers

The differentiation between a necessity (through outside or internal forces) versus an opportunity to generate value-adding applications (Pierce and Delbecq, 1977) is a relevant distinction. While the former is brought about by pressure, the latter emerges through an innovative corporate mindset. However, we find no clear evidence whether this distinction results in varying implementation success.

Being DA-driven indicates a resource-oriented perspective. These projects consider existing, un- or underused data in the company with which value-adding products could be built or analyses executed. From there, other data silos that could be connected are considered to eventually build an SCA prototype.

An SI-driven implementation is usually supported by a concrete business case, which makes the argument for the use case easier and more data-driven (Marilex, Llave and Olsen, 2018). SI can refer to multiple different issues that are familiar from other IT applications within SCM, such as decreasing high costs of an operational process or reducing human error (He and Chen, 2008). SI is connected with performance expectancy, which is the perceived prospect of an individual employee to generate some benefit in their job-related activities through use of the technology (Queiroz and Wamba, 2019). Our experts expand this concept, including the perspectives of managers or other stakeholders that might not be directly impacted by the operational use, but still see the potential to alleviate a particular issue through the use of SCA. Looking at the more general case of drivers for IT usage in SCM, (He and Chen) point out some specific drivers that would fall in our SI category and that were also mentioned by our experts, such as cost reduction regarding an operational process or reduction of human errors.

Supply Chain Analytics Implementation

Looking at technologically-driven projects, (Paolini and Fili, 2017) also identify technological development as an SCA driver, the concrete underlying aim however is not reflected upon. Our experts focus particularly on building knowledge as well as communicating the technology usage internally and externally. We condense these into TI and TE. TI is primarily concerned with building up technological know-how, generating buy-in from the employees, and developing a data-driven company culture. This is seen as strengthening the setup of the corporation as a technological leader beyond either the specific technology (TI and TE often aim to also include other technologies beyond SCA) or the specific use case. Creating a *sense of urgency* for employees additionally makes it easier to generate commitment for future projects by ideally producing results that can be referred to when building broader use cases. However, both TI and TE often extenuate the focus on a business case (though of course projects are preferred were such a positive case can be made, but this is not the underlying driver). TI-driven ventures are consequently often linked to the first steps a company takes in the field of SCA. TE focusses on the outside perception of the corporation, aiming to build an image of an advanced technological leader to attract talent or signal to customers.

Transparency is a common pursuit of SCA initiatives in SCM (Zhu, et al., 2018). Aiming to provide a clearer understanding of the status of their supply chain and consider emerging risks swiftly and efficiently, TR is described by the interviewees as a driver that emerges often from a “bad gut feeling”. This entails the intuition of not being able to build an accurate picture of the issues (TR is primarily issue-driven rather than opportunity-driven) in the supply chain.

Drivers such as CO and PA are faced by all kinds of businesses, relating to various technologies (Khan, Amin and Lambrou). CO is described by our interviewees as the necessity to close the gap towards competitors, who have built products and services out of their SCA capabilities or simply have become more efficient and thus more competitive. This external pressure is felt and drives SCA efforts.

The driver PA is related to social influence, which is described by (Queiroz and Wamba, 2019) in the context of Blockchain. The often implicit and indirect notion of social influence however is not stressed by our interviewees. Instead, quite direct inquiries by external stakeholders are related, especially from customers and supply chain partners.

The latter case occurs frequently, since some SCA use cases rely on upstream or downstream data from suppliers or customers to achieve their full potential. Since the ambition of a single firm is thus linked to their partners also providing high-quality data, the step for these linked companies to also establish SCA use cases (corresponding to our PA driver) is natural.

It should be emphasized, that no project is uniquely driven by one of our mentioned drivers. In practice, different drivers occur for the same project.

Merging our research streams of adoption drivers and CSF for SCA, we find evidence for varying relevance of CSF for different drivers in our qualitative data set. Our evidence indicates that it is particularly important to consider CSF from a different context than the driver. E.g. a DA driven project often already considers technological CSF sufficiently, but lacks understanding of the other, equally relevant areas. Our suggestion is thus to emphasize ones focus on organizational and environmental CSF when conducting a technologically driven SCA initiative. Correspondingly, the respective other contexts are to be emphasized for organizationally and environmentally driven undertakings.

We do not mean to indicate that some CSF are of lesser importance – of course, it is essential to also look at data quality and infrastructure even when the project is considered technologically driven. Our experts indicate, however, that these are considered in a disproportionately high manner, which means looking at the other areas seems to increase success probability during implementation.

6 Conclusion

Our results are twofold. First, we find that the CSF provided by literature are not consistently considered by the SCM practitioners we interviewed. There is a focus on technological factors, whereas CSF in the categories Organization and Environment are neglected more often. This is particularly the case in technologically driven SCA projects. This leads us to our second finding: Prioritizing CSF depending on the underlying drivers seems to increase likelihood for implementation success. Notably, emphasizing the area the project is not driven from seems to have additional value.

Supply Chain Analytics Implementation

Reflecting on our limitations, we build our insights on a set of qualitative expert interview which, while in-depth and useful to identify thinking patterns and reasons of the interviewees, is too small a sample to provide reliable conclusions for a universal perspective. We do however include experts from diverse industries, indicating the potential to extract comprehensive patterns from our approach in the future.

Looking toward future research, providing further evidence for our findings via a quantitative study is necessary to establish the links between drivers and CSF on a broader sample size.

References

- Ajzen, I., 1985. From intentions to actions: A theory of planned behavior. In: 1985. Action control: Springer, pp. 11–39.
- Ajzen, I., 1991. The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2), pp. 179–211.
- Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R. and Childe, S. J., 2016. How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, 182, pp. 113–131.
- Alahakoon, D. and Yu, X., 2013. Advanced analytics for harnessing the power of smart meter big data. In: 2013. 2013 IEEE International Workshop, pp. 40–45.
- Alles, M. G., 2015. Drivers of the use and facilitators and obstacles of the evolution of big data by the audit profession. *Accounting Horizons*, 29(2), pp. 439–449.
- Bhattacharya, M. and Wamba, S. F., 2018. A conceptual framework of RFID adoption in retail using TOE framework. In: 2018. *Technology Adoption and Social Issues: Concepts, Methodologies, Tools, and Applications*. Hershey PA: IGI Global, pp. 69–102.
- Boynton, A. C. and Zmud, R. W., 1984. An assessment of critical success factors. *Sloan management review*, 25(4), pp. 17–27.
- Brinch, M., 2018a. Understanding the value of big data in supply chain management and its business processes: Towards a conceptual framework. *International Journal of Operations and Production Management*, [e-journal] 38(7), pp. 1589–1614. <http://dx.doi.org/10.1108/IJOPM-05-2017-0268>.
- Brinch, M., 2018b. Understanding the value of big data in supply chain management and its business processes. *International Journal of Operations & Production Management*, [e-journal] 38(7), pp. 1589–1614. <http://dx.doi.org/10.1108/IJOPM-05-2017-0268>.
- Brynjolfsson, E., Hitt, L. M. and Kim, H. H., 2011. Strength in numbers: How does data-driven decisionmaking affect firm performance? SSRN Working Paper. <Available at SSRN: <http://ssrn.com/abstract=1819486>>.

Supply Chain Analytics Implementation

- Chan, F. T. and Chong, A. Y.-L., 2013. Determinants of mobile supply chain management system diffusion: a structural equation analysis of manufacturing firms. *International Journal of Production Research*, [e-journal] 51(4), pp. 1196–1213. <http://dx.doi.org/10.1080/00207543.2012.693961>.
- Cokins, G., 2013. Driving acceptance and adoption of business analytics. *Journal of Corporate Accounting & Finance*, 24(2), pp. 69–74.
- Damanpour, F. and Schneider, M., 2006. Phases of the adoption of innovation in organizations: effects of environment, organization and top managers 1. *British journal of Management*, 17(3), pp. 215–236.
- Davenport, T. H., 2006. Competing on analytics. *harvard business review*, 84(1), pp. 98–107.
- Davis, F. D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, pp. 319–340.
- Denolf, J. M., Trienekens, J. H., Wognum, P. N., Schütz, V., Van Der Vorst, Jack GAJ and Omta, S. O., 2018. “Actionable” critical success factors for supply chain information system implementations. *International Journal on Food System Dynamics*, 9(1), pp. 79–100.
- Depietro, R., Wiarda, E. and Fleischer, M., 1990. The context for change: Organization, technology and environment. In: L. G. Tornatzky, and M. Fleischer, eds. 1990. *The processes of technological innovation*. Lexington, MA.: Lexington Books, pp. 151–175.
- Fernandez Molanes, R., Amarasinghe, K., Rodriguez-Andina, J. and Manic, M., 2018. Deep learning and reconfigurable platforms in the Internet of Things: Challenges and opportunities in algorithms and hardware. *IEEE Industrial Electronics Magazine*, 12(2).
- Fichman, R. G., 1992. Information technology diffusion: a review of empirical research. In: J. I. Gross, J. D. Becker, and J. J. Elam, eds. 1992. *Proceedings of the 13th International Conference on Information Systems*. Dallas, TX.
- Gao, J., Koronios, A. and Selle, S., 2015. Towards a process view on critical success factors in big data analytics projects, pp. 1–14.

- Gao, Y. and Mosalam, K. M., 2018. Deep transfer learning for image-based structural damage recognition. *Computer-Aided Civil and Infrastructure Engineering*, 33(9), pp. 748–768.
- Gröger, C., 2018. Building an industry 4.0 analytics platform. *Datenbank-Spektrum*, 18(1), pp. 5–14.
- Haenecke, H., 2002. Methodenorientierte Systematisierung der Kritik an der Erfolgsfaktorenforschung. *Zeitschrift für Betriebswirtschaft*, 72(2), pp. 165–183.
- Hameed, M. A., Counsell, S. and Swift, S., 2012. A conceptual model for the process of IT innovation adoption in organizations. *Journal of Engineering and Technology Management*, 29(3), pp. 358–390.
- He, M. and Chen, J. The drivers for information technology application in supply chain management: How developing countries' companies facing globalization. In: 2008 3rd IEEE Conference on Industrial Electronics and Applications: IEEE, pp. 2306–2311.
- He, M. and Chen, J., 2008. The drivers for information technology application in supply chain management: How developing countries' companies facing globalization. In: 2008 3rd IEEE Conference on Industrial Electronics and Applications: IEEE, pp. 2306–2311.
- Hellingrath, B. and Lechtenberg, S., 2019. Applications of Artificial Intelligence in Supply Chain Management and Logistics: Focusing Onto Recognition for Supply Chain Execution. In: 2019. *The Art of Structuring*: Springer, pp. 283–296.
- Ilie-Zudor, E., Ekárt, A., Kemeny, Z., Buckingham, C., Welch, P. and Monostori, L., 2015. Advanced predictive-analysis-based decision support for collaborative logistics networks. *Supply Chain Management: An International Journal*, 20(4), pp. 369–388.
- Kache, F. and Seuring, S., 2017. Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal of Operations and Production Management*, 37(1), pp. 10–36.

Supply Chain Analytics Implementation

- Kamal, M. M., 2006. IT innovation adoption in the government sector: identifying the critical success factors. *Journal of Enterprise Information Management*, 19(2), pp. 192–222.
- Kersten, W., Seiter, M., See, B. von, Hackius, N. and Maurer, T., 2017. Chancen der digitalen Transformation: Trends und Strategien in Logistik und Supply Chain Management. Hamburg: DVV Media Group GmbH.
- Khan, A. M. A., Amin, N. and Lambrou, N. Drivers and barriers to business intelligence adoption: A case of Pakistan. In: *Proceedings of the European and Mediterranean Conference on Information Systems (EMCIS2010)*, Abu Dhabi, UAE, pp. 1–23.
- Kim, S. and Garrison, G., 2010. Understanding users' behaviors regarding supply chain technology: Determinants impacting the adoption and implementation of RFID technology in South Korea. *International Journal of Information Management*, 30(5), pp. 388–398.
- Kwon, O., Lee, N. and Shin, B., 2014. Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management*, [e-journal] 34(3), pp. 387–394. <http://dx.doi.org/10.1016/j.ijinfomgt.2014.02.002>.
- Kwon, T. H. and Zmud, R. W., 1987. Unifying the fragmented models of information systems implementation. In: R. J. Boland Jr, and Hirschheim R. A., eds. 1987. *Critical Issues in Information Systems Research*. New York: Wiley.
- Lamba, K. and Singh, S. P., 2018. Modeling big data enablers for operations and supply chain management. *The International Journal of Logistics Management*, [e-journal] 29(2), pp. 629–658. <http://dx.doi.org/10.1108/IJLM-07-2017-0183>.
- Landing AI, 2018. AI Transformation Playbook: How to lead your company into the AI era. [online] Available at: <<https://landing.ai/ai-transformation-playbook/>>.
- Lewin, K., 1947. Frontiers in group dynamics: Concept, method and reality in social science; social equilibria and social change. *Human relations*, 1(1), pp. 5–41.
- Lin, D., Lee, C. K. and Lin, K. Research on effect factors evaluation of internet of things (IOT) adoption in Chinese agricultural supply chain. In: 2016 IEEE International

Conference on Industrial Engineering and Engineering Management (IEEM): IEEE, pp. 612–615.

Lodemann, S. and Kersten, W., 2020. Identifikation und Umsetzung der Potenziale von Data Analytics im Supply Chain Management. *Mittelstand-Digital Magazin Wissenschaft trifft Praxis*, (13), 22-29.

Lu, H., Li, Y., Chen, M., Kim, H. and Serikawa, S., 2018. Brain intelligence: go beyond artificial intelligence. *Mobile Networks and Applications*, 23(2), pp. 368–375.

Marilex, R., Llave, M. and Olsen, D., 2018. Drivers of Business Intelligence-based Value Creation: The Experts' View. *Mediterranean Conference on Information Systems (MCIS)*, 13.

Matta, V., Koonce, D. and Jeyaraj, A., 2012. Initiation, experimentation, implementation of innovations: The case for radio frequency identification systems. *International Journal of Information Management*, 32(2), pp. 164–174.

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J. and Barton, D., 2012. Big data: the management revolution. *harvard business review*, 90(10), pp. 60–68.

Michael, P., 1985. *Competitive advantage: creating and sustaining superior performance*. New York: Free Press.

Moktadir, M. A., Ali, S. M., Paul, S. K. and Shukla, N., 2019. Barriers to big data analytics in manufacturing supply chains: A case study from Bangladesh. *Computers & Industrial Engineering*, [e-journal] 128, pp. 1063–1075. <http://dx.doi.org/10.1016/j.cie.2018.04.013>.

Müller, R. and Jugdev, K., 2012. Critical success factors in projects: Pinto, Slevin, and Prescott-the elucidation of project success. *International Journal of Managing Projects in Business*, 5(4), pp. 757–775.

Nam, D., Lee, J. and Lee, H., 2019. Business analytics adoption process: An innovation diffusion perspective. *International Journal of Information Management*, 49, pp. 411–423.

NewVantagePartners, Bean, R. and Davenport, T. H., 2018. *Big Data Executive Survey 2018*. [online] Available at: <<http://newvantage.com/wp>

Supply Chain Analytics Implementation

content/uploads/2018/01/Big-Data-Executive-Survey-2018-Findings-1.pdf>
[Accessed 20 February 2020].

- Oliveira, T. and Martins, M. F., 2011. Literature review of information technology adoption models at firm level. *Electronic Journal of Information Systems Evaluation*, 14(1), p. 110–110.
- Paolini, M. and Fili, S., 2017. How to benefit from big data and network complexity. [online] Available at: <http://content.rcrwireless.com/20170620_Mastering_Analytics_Report> [Accessed 20 February 2020].
- Patton, M. Q., 2002. *Qualitative research and evaluation methods*.
- Pierce, J. L. and Delbecq, A. L., 1977. Organization structure, individual attitudes and innovation. *Academy of management review*, 2(1), pp. 27–37.
- Queiroz, M. M. and Telles, R., 2018. Big data analytics in supply chain and logistics: an empirical approach. *The International Journal of Logistics Management*, [e-journal] 29(2), pp. 767–783. <http://dx.doi.org/10.1108/IJLM-05-2017-0116>.
- Queiroz, M. M. and Wamba, S. F., 2019. Blockchain adoption challenges in supply chain: An empirical investigation of the main drivers in India and the USA. *International Journal of Information Management*, 46, pp. 70–82.
- Raman, S., Patwa, N., Niranjana, I., Ranjan, U., Moorthy, K. and Mehta, A., 2018. Impact of big data on supply chain management. *International Journal of Logistics Research and Applications*, 21(6), pp. 579–596.
- Richey, R. G., Morgan, T. R., Lindsey-Hall, K. and Adams, F. G., 2016. A global exploration of Big Data in the supply chain. *International Journal of Physical Distribution & Logistics Management*, [e-journal] 46(8), pp. 710–739. <http://dx.doi.org/10.1108/IJPDLM-05-2016-0134>.
- Rogers, E. M., 2003. *Diffusion of innovations: Simon and Schuster*.
- Rozados, I. V. and Tjahjono, B., 2014. Big data analytics in supply chain management: Trends and related research. 6th International Conference on Operations and Supply Chain Management.

- Sanders, N. R., 2016. How to Use Big Data to Drive Your Supply Chain. *California Management Review*, [e-journal] 58(3), pp. 26–48.
<http://dx.doi.org/10.1525/cmr.2016.58.3.26>.
- Schoenherr, T. and Speier-Pero, C., 2015a. Data Science, Predictive Analytics, and Big Data in Supply Chain Management: Current State and Future Potential. *Journal of Business Logistics*, [e-journal] 36(1), pp. 120–132.
<http://dx.doi.org/10.1111/jbl.12082>.
- Schoenherr, T. and Speier-Pero, C., 2015b. Data Science, Predictive Analytics, and Big Data in Supply Chain Management: Current State and Future Potential. *Journal of Business Logistics*, [e-journal] 36(1), pp. 120–132.
<http://dx.doi.org/10.1111/jbl.12082>.
- Schreier, M., 2014. Varianten qualitativer Inhaltsanalyse: Ein Wegweiser im Dickicht der Begrifflichkeiten. *Forum Qualitative Sozialforschung*, 15(1).
- Shen, B. and Chan, H.-L., 2017. Forecast Information Sharing for Managing Supply Chains in the Big Data Era: Recent Development and Future Research. *Asia-Pacific Journal of Operational Research*, [e-journal] 34(01), p. 1740001–1740001.
<http://dx.doi.org/10.1142/S0217595917400012>.
- Thong, J. Y. L., 1999. An integrated model of information systems adoption in small businesses. *Journal of Management Information Systems*, 15(4), pp. 187–214.
- Venkatesh, V., Morris, M. G., Davis, G. B. and Davis, F. D., 2003. User acceptance of information technology: Toward a unified view. *MIS quarterly*, pp. 425–478.
- Venkatesh, V., Thong, J. Y. L. and Xu, X., 2012. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, pp. 157–178.
- Waller, M. A. and Fawcett, S. E., 2013. Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management. *Journal of Business Logistics*, [e-journal] 34(2), pp. 77–84.
<http://dx.doi.org/10.1111/jbl.12010>.

Supply Chain Analytics Implementation

- Wamba, S. F., Akter, S., Edwards, A., Chopin, G. and Gnanzou, D., 2015. How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, 165, pp. 234–246.
- Wang, G., Gunasekaran, A., Ngai, E. W. and Papadopoulos, T., 2016. Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, [e-journal] 176, pp. 98–110. <http://dx.doi.org/10.1016/j.ijpe.2016.03.014>.
- Wanigasekara, C., Swain, A., Nguang, S. K. and Prusty, B. G. Improved Learning from Small Data Sets Through Effective Combination of Machine Learning Tools with VSG Techniques. In: 2018 International Joint Conference on Neural Networks (IJCNN): IEEE, pp. 1–6.
- Wuest, T., Weimer, D., Irgens, C. and Thoben, K.-D., 2016. Machine learning in manufacturing: advantages, challenges, and applications. *Production & Manufacturing Research*, [e-journal] 4(1), pp. 23–45. <http://dx.doi.org/10.1080/21693277.2016.1192517>.
- Zhou, Z.-H., 2016. Learnware: on the future of machine learning. *Frontiers Comput. Sci.*, 10(4), pp. 589–590.
- Zhu, S., Song, J., Hazen, B. T., Lee, K. and Cegielski, C., 2018. How supply chain analytics enables operational supply chain transparency. *International Journal of Physical Distribution & Logistics Management*, pp. 47–68.