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Managing Supply Chain Analytics – Guiding organizations to execute Analytics initiatives in Logistics and Supply Chain Management

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Abstract

The application of Analytics in the domain of Logistics and Supply Chain Management (LSCM) – Supply Chain Analytics (SCA) – presents a wide range of advantages. The domain has historically been a first mover in the application of analytical methods due to the complex decision-making under uncertainty and has the potential to exploit manifold new data sources accessible through recent technological advances. Scholars have provided evidence for the performance increase in this domain due to Analytics and have also argued for competitive advantages enabled through it. Surveys amongst practitioners and reports show similar potential to improve the efficiency of processes, create new business opportunities with it and eventually increase customer orientation. However, LSCM organizations are not extensively and comprehensively utilizing these potential advantages and the value and benefits resulting from it. Organizations are either prevented to take advantage through barriers, or they disbelieve in the advantages and behave reluctant, while new competitors exploit Analytics to gain market share. These issues demonstrate that executing Analytics initiatives goes beyond the application of analytical methods and requires supporting and directing managerial actions. This thesis investigates these managerial actions and practices for Analytics initiatives in LSCM. Thereby, initiative describes the entire lifecycle of Analytics solutions, from the definition of the problem to be solved and its development to its use and maintenance in the value-added processes. With a variety of research methods, including Grounded Theory, Clustering, Case Studies, and the Q-Methodology, this thesis examines SCA initiatives in exploratory and confirmatory research designs. In four articles, investigations are conducted of (1) characteristics distinguishing LSCM from other domains in the execution of Analytics, (2) Analytics initiatives currently executed in LSCM, (3) the process of executing Analytics initiatives in LSCM to gain valuable Analytics solutions, and (4) barriers LSCM organizations encounter in the execution of Analytics initiatives and the measures they employ to overcome the barriers. These articles result in a map of characteristics to distinguish domains in the execution of Analytics initiatives and an individual profile of LSCM, six distinct Archetypes of SCA initiatives, comprehensive explanations of the competitive advantage from Analytics in LSCM, and frameworks of barriers and measures in SCA. The individual results of each article are used to describe the value LSCM organizations can create for their customers, and by further combining the results of the articles with 15 process approaches to manage

Analytics initiatives, a supplemented approach to manage Analytics initiatives, especially SCA initiatives, is developed. In this pursuit, Analytics is established as a tool, that requires human creativity and expertise to unfold its full potential. As such a tool, it provides solutions to support humans in their decision-making and can lead to improved decisions if, like any other tool, it is applied in the appropriate approach. With the research results described above, this thesis provides *guidance* for managers in LSCM to manage SCA initiatives such that they understand this appropriate approach for Analytics in LSCM and are enabled to employ it for (competitive) advantage and continuous improvements of processes and customer satisfaction.

Zusammenfassung

Die Anwendung von Analytics in der Logistik und Supply Chain Management (LSCM) Domäne – Supply Chain Analytics (SCA) – bietet eine Vielzahl von Vorteilen. Die Domäne war in der Vergangenheit aufgrund der komplexen Entscheidungsfindung unter Unsicherheit ein „First Mover" bei der Anwendung analytischer Methoden und verfügt über das Potenzial, die zahlreichen neuen Datenquellen ertragreich zu nutzen, die durch die jüngsten technologischen Fortschritte zugänglich sind. Die wissenschaftliche Literatur hat Belege für die Leistungssteigerung in der LSCM Domäne durch Analytics erbracht und auch für Wettbewerbsvorteile argumentiert, die durch sie ermöglicht werden. Umfragen unter Praktikern und Berichte zeigen ein ähnliches Potenzial, die Effizienz von Prozessen zu verbessern, damit neue Geschäftsmöglichkeiten zu schaffen und schließlich die Kundenorientierung zu erhöhen. LSCM-Organisationen nutzen diese potenziellen Vorteile jedoch nicht umfassend aus und erschließen somit den daraus resultierenden Wert und Nutzen nicht im vollen Umfang. Unternehmen werden entweder durch Barrieren daran gehindert, die Vorteile auszunutzen, oder sie glauben nicht an die Vorteile und verhalten sich zögerlich, während neue Wettbewerber Analytics einsetzen, um Marktanteile zu gewinnen. Diese Probleme zeigen, dass die Durchführung von Analytics-Initiativen über die Anwendung von Analysemethoden hinausgeht und die Unterstützung und Steuerung von Managementmaßnahmen erfordert. Diese Arbeit untersucht diese Managementmaßnahmen und -praktiken für Analytics-Initiativen in der LSCM Domäne. Dabei beschreibt Initiative den gesamten Lebenszyklus von Analytics-Lösungen, von der Definition des zu lösenden Problems, über die Lösungsentwicklung bis hin zu dessen Einsatz und Wartung in den Wertschöpfungsprozessen. Mit einer Vielzahl von Forschungsmethoden, einschließlich Grounded Theory, Clustering, Case Studies und der Q-Methodik, untersucht diese Arbeit SCA-Initiativen in explorativen und konfirmatorischen Forschungsdesigns. In vier wissenschaftlichen Artikeln werden Untersuchungen durchgeführt zu (1) Merkmalen, die LSCM von anderen Domänen bei der Durchführung von Analytics-Initiativen abgrenzt, (2) Analytics-Initiativen, die derzeit in der LSCM Domäne durchgeführt werden, (3) dem Prozess der Ausführung von Analytics-Initiativen in LSCM, um wertvolle Analytics-Lösungen zu schaffen, und (4) Barrieren, auf die LSCM-Organisationen bei der Durchführung von Analytics-Initiativen treffen und den Maßnahmen, die sie anwenden, um die Barrieren zu überwinden. Diese Artikel haben resultiert in kartografierten Merkmalen zur Unterscheidung von Domänen

bei der Durchführung von Analytics-Initiativen und einem individuellen Profil von LSCM bezüglich dieser Merkmale; sechs abgegrenzten Archetypen von SCA-Initiativen; umfassenden Erklärungen der Erlangung von Wettbewerbsvorteile durch Analytics in LSCM; sowie Rahmenkonzepte von Barrieren und Maßnahmen in SCA. Einerseits werden die Ergebnisse der einzelnen Artikel dazu verwendet, um den Wert zu beschreiben, den LSCM-Organisationen für ihre Kunden schaffen können. Andererseits wird durch die weiterführende Kombination der Ergebnisse der Artikel mit 15 Prozessansätzen zum Management von Analytics-Initiativen ein ergänzender Ansatz zum Management von Analytics-Initiativen, insbesondere von SCA-Initiativen, entwickelt. In diesem Bestreben etabliert diese Arbeit Analytics als ein Werkzeug, das menschliche Kreativität und Expertise erfordert, um sein volles Potenzial zu entfalten. Als solches Werkzeug bietet es Lösungen zur Unterstützung des Menschen bei seiner Entscheidungsfindung und kann zu verbesserten Entscheidungen führen, wenn es wie jedes andere Werkzeug im geeigneten Ansatz eingesetzt wird. Mit den oben beschriebenen Forschungsergebnissen bietet diese Arbeit *Anleitung* für Manager in LSCM, um SCA-Initiativen so zu managen, dass sie diesen geeigneten Ansatz für Analytics in LSCM verstehen und in die Lage versetzt werden, ihn für (Wettbewerbs-) Vorteile und kontinuierliche Verbesserungen der Prozesse und der Kundenzufriedenheit einzusetzen.

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Abbreviations

AI	Artificial Intelligence
AO	Category: Analytics objective
CRISP-DM	Cross-industry standard process for data mining
DALM	Data analytics lifecycle model
DAT	Category: Data management
EDI	Electronic Data Interchange
e.g.	For example
ERP	Enterprise Resource Planning
ETA	Estimated-time-of-arrival
GPS	Global Positioning System
GSM	Global System for Mobile Communications
HUM	Category: Human involvement
IoT	Internet-of-Things
IT	Information technology
KBV	Knowledge-based view
LSCM	Logistics and Supply Chain Management
LSP	Logistics service provider
min.	Minimum
N/A	Not available
No.	Numero
OEM	Original Equipment Manufacturer
PADIE	process-application-data-insight-embed
RFID	Radio-frequency identification
RO	Research objective
SCA	Supply Chain Analytics
SCO	Category: Supply Chain objective
SCOR	Supply Chain Operations Reference
sCRISP-A	Supplemented CRISP-DM for Analytics initiatives
SEMMA	Sample, Explore, Modify, Model, and Assess

SEP	Strategy execution process
TA	Category: Type of Analytics
TEC	Category: Technological aspects
TSP	Theory on structuring problems
UPGMA	Unweighted Pair Group Method with Arithmetic Mean
VOIP	Voice over Internet Protocol
WPGMA	Weighted Pair Group Method with Arithmetic Mean
yrs.	Years

1 Introduction

"The purpose of computing is insight, not numbers" is the motto of Richard W. Hamming's book "Numerical methods for scientists and engineers" (1962, p. 395), which covers problem solving with the help of computing for scientists and engineers. The book is an early example of modelling and data analysis that goes beyond the question of calculating and raises concerns about the purpose of calculations. The author highlights that computing may not only answer questions, but rather can help to gain understanding of the situation around the question that is examined. He indicates a residual to be handled – a lack of knowledge about the purpose of the calculation – and a problem proposer who may not exactly know, what he wants. In the light of this thesis, the lacking knowledge may include the actual problem, the applicability of the solution or whether a user would actually apply the solution. These issues, which are managerial instead of numerical, are similarly occurring for Supply Chain Analytics and are under investigation in this thesis.

1.1 Research Motivation

During the research for this thesis and a short-lived timespan before it, a large body of research about Analytics in Logistics and Supply Chain Management (LSCM) emerged, motivating this thesis. To preemptively summarize the subsequently presented research motivation, Analytics composes a field full of potential to reduce costs, improve efficiency and enable new courses for actions for organizations in LSCM. However, it is a complex field with technological, organizational and human-based drivers of complexity leading to a vast variety of barriers and reluctance hindering the successful realization of the desired benefits and creation of value or rather valuable solutions. Thus, this thesis does not intend to develop further new technological solutions, algorithms or models, organizations may equally be obstructed and reluctant to apply. The **motivation** of this thesis, founded on the subsequent section, is to gain understanding and insights on these barriers, the reluctance and the requirements to enable benefits from Analytics. Based on understanding and insights, this thesis intends to provide organizations in LSCM and organizations executing LSCM activities with means to identify, comprehend and control these drivers of complexity. Consequently, the motivation is to enable them to successfully use Analytics, realize the desired benefits and generate valuable solutions, such that they can create sustainable competitive advantage and continuous improvement. In summary, this thesis focusses on means and practices of the management of Analytics in LSCM – the management of "Supply Chain Analytics" (SCA).

1.1.1 Theoretical Motivation

Prior to discussing the body of research, a short notice on taxonomy is necessary. For the purpose of research on management of Analytics, the terms Analytics, Data Science, Big Data (Analytics) and Artificial Intelligence (AI) are considered as synonyms. As will be discussed in section 2.2, these terms show differences in the foundational technologies or the deployed analytical methods but are identically based on the analysis of data to impact decision-making in organizations and display similar organizational effects and barriers. Hence, the terms are regarded synonymous in this thesis for their objective to create value from data.

The following discussion on theoretical motivation considers scientific literature on theoretical arguments and inference from usually smaller samples (e.g., case studies and small sample surveys). From this literature, the extracted aspects of eligibility, accessibility, performance increase, competitive advantage, and barriers have been extracted.

A primary consideration has to be, whether the domain of LSCM is eligible to adopt and apply Analytics. Thereby, **eligibility** is supposed to describe whether the domain meets the requirements and has a need for Analytics. The relationship between Analytics and LSCM has been emphasized in the literature from various points of view. LSCM is considered as an early adopter and traditional user of analytical methods such as statistical forecasting and Operations Research (Chae, Olson, et al., 2014; Davenport, 2009; Matthias et al., 2017; Sanders, 2016; Souza, 2014). LSCM has developed into a knowledge-based domain relying on data and analytics for better decision-making. Additionally, many activities in LSCM focus on exploitation of data (Brinch et al., 2018; Trkman et al., 2010). A variety of activities benefit from Analytics and accurate provision of data, since the decisions in these activities are rich in optional actions and requirements to be considered, as well as their trade-offs (Chae, Yang, et al., 2014; Souza, 2014; Wang et al., 2016). In addition, the demand for Analytics in LSCM is growing due to increases in the complexity of decision-making caused by increased competition, uncertainty, customization, need for sustainability and globalization (Chae, Yang, et al., 2014; Lai et al., 2018; Roßmann et al., 2018). The domain of LSCM is also considered as data intense due to producing a lot of operational data per organization which are eventually shared in collaborative activities with business models (e.g., forth-party logistics providers) completely reliant on data exchange for coordination, planning and integration of shared logistical tasks (Chae, Yang, et al., 2014; Dutta and Bose, 2015; Hopkins and Hawking, 2018; Ludwig, 2014). This makes LSCM a good fit for Analytics. This characteristic has been recognized by practitioners for its potential of high returns for organizations (Jeske et al., 2013; Kiron et al., 2012; Lavalle et al., 2011). Further, an achieved increase in performance may eventually improve the performance of supply chain partners (Oliveira et al., 2012; Richey et al., 2016). In summary, LSCM is very well suited to employ quantitative methods from Analytics to exploit data.

The aspect of **accessibility** shall describe the technological changes that enable new opportunities for creating value from Analytics in LSCM and, of course, in other domains. The most famous component of this, is the huge amount of data collected today, since a considerable number of publications on SCA mentions the newest projection of the worldwide amount of data in some future year (e.g., Chae, Yang, et al., 2014; Roßmann et al., 2018). The increasing ease of collecting data has led to an increase of collected data in LSCM as well (Schoenherr and Speier-Pero, 2015; Waller and Fawcett, 2013). Along the process, data is collected from all sorts of sources including GPS sensors, RFID sensors creatively used in various forms, mobile devices, transactional IT systems, point-of-sales devices, different forms of scanners, and increasingly from machines and assets which are delivered with data collection abilities through several sensors sending status and performance (Kache and Seuring, 2017; Matthias et al., 2017; Richey et al., 2016; Sanders, 2016; Souza, 2014; Wang et al., 2016). Additionally, data may come from external sources such as data exchange with partners and customers, social media, customer feedback, or external signals such as traffic conditions (Kache and Seuring, 2017; Matthias et al., 2017; Sanders, 2016; Srinivasan and Swink, 2018). Besides data collection, the exchange of data has improved especially in velocity due to the internet giving real-time abilities in an internet speed like information exchange internally and externally (Kache and Seuring, 2017; Sanders, 2016; Wang et al., 2016). Finally, technologies and methods have improved. Methods for analyzing data have had large developments, especially in machine learning techniques to exploit the larger amount of data and sources (Chae, Olson, et al., 2014; Sanders, 2016; Waller and Fawcett, 2013). Technologies like in-memory databases, virtualization ("cloud computing") and distributed computing (e.g., Hadoop) provide the technical abilities to exploit the data (Hahn and Packowski, 2015; Hopkins and Hawking, 2018; Roßmann et al., 2018).

The review of scientific literature presented an extensive potential for the **performance increase** of LSCM activities. However, taking a deeper look, most effects are indirect from better and more frequent visibility, gained transparency into the past, present and future, and resulting decision-making. Having an extensively transparent insight into past performance, issues, failures/unwanted behavior of assets or employees, costs of activities and suppliers, bottlenecks as well as all ongoing activities along the supply chain allows to identify improvement potential and distribute resources in a more efficient way (Brinch et al., 2018; Chae, Yang, et al., 2014; Dutta and Bose, 2015; Sanders, 2016; Wang et al., 2016; Zhu et al., 2018). This is key to mastering the increasing challenging environment for logistics, such as dense urban areas (Straube, Reipert, et al., 2017). Visibility about the future due to forecasts and improved understanding of uncertainties in supply, demand and costs allows to create better and optimized plans for improved utilization (effectiveness) with reduced slack resources and expensive reactions (e.g., safety stocks, overtime, expedited shipments, markdowns) (Hazen et al., 2014; Richey et al., 2016; Roßmann et al., 2018; Sanders, 2016; Srinivasan and Swink, 2018). Finally, monitoring the present actions in real-time allows dynamic decision-making for faster reactions to changing market conditions, changing needs of customers, and suppliers, degrading performance and incidents with subsequently faster corrective actions and shorter downtime (Chavez et al., 2017; Dutta and Bose, 2015; Kache and Seuring, 2017; Wang et al., 2016; Zhu et al., 2018) Given that improved decisions are made from this transparency and visibility, improving efficiency, utilization and time, it eventually leads to reduced costs (Dutta and Bose, 2015; Kache and Seuring, 2017; Richey et al., 2016) as an indirect effect from Analytics applied to LSCM. An important concluding point is that Analytics effects are indirect by enabling and triggering actions with improved outcome (Chae, Yang, et al., 2014) and thus do not guarantee performance increase from investments in Analytics if process flexibility and process maturity do not allow to execute the actions (Oliveira et al., 2012; Srinivasan and Swink, 2018). There is no performance increase from analyzing data itself, what makes measuring Analytics impact on LSCM performance difficult.

Research has also argued for the **competitive advantage** created from adopting Analytics in LSCM. Scholars have argued for competitive advantage based on observing performance increase, gained market share, and improved management decisions – generally an improved position in competition – after investing and adopting Analytics to LSCM (Dutta and Bose, 2015; Matthias et al., 2017; Oliveira et al., 2012). Adding to this list is the strategic opportunity for improved differentiation from competitors, which is, however, not directly labeled as competitive advantage (Roßmann et al., 2018). It has been argued, that SCA itself is a resource, which is valuable, inimitable, and non-substitutable and thus is resultingly a source of sustained competitive advantage (Chae, Olson, et al., 2014). Furthermore, scholars argue it to be a second order support or driver of capabilities, which generate competitive advantage. This includes manufacturing capabilities, represented by the ability to manufacture goods of high quality, flexible and with low costs for customer satisfaction, as well as effectiveness and efficiency capabilities, and innovation capabilities (Chavez et al., 2017; Hopkins and Hawking, 2018; Trkman et al., 2010). However, these interpretations of the impact of Analytics to LSCM are theoretical.

As indicated above, adopting and applying Analytics is no sure-fire success. There are **barriers** and challenges to using it in LSCM and, thus, obstruct the benefits explained above, and managers require guidance to overcome these barriers. An extensive discussion on barriers follows in a later part of this thesis. As a preliminary review, it shall be emphasized, that barriers are observable at multiple stages and influencing multiple resources. On a management level, commitment and knowledge might be missing (Lai et al., 2018; Richey et al., 2016). On an operational level, the employees might be inexperienced with Analytics, uncreative about using data to their advantage, or unable to explain the value of their ideas (Kache and Seuring, 2017; Sanders, 2016; Schoenherr and Speier-Pero, 2015). On a cultural level, a lack of openness to new data driven solutions may exist, possibly a strong unwillingness against it (Dutta and Bose, 2015; Richey et al., 2016). Concerning resources, IT systems' readiness for Analytics or rather the ability to integrate the systems' data might be missing (Kache and Seuring, 2017; Richey et al., 2016; Schoenherr and Speier-Pero, 2015). The data, which are core to Analytics, might not be available or have a bad quality, resulting in inaccurate or faulty analyses (Hazen et al., 2014; Schoenherr and Speier-Pero, 2015). Finally, the physical process may not be ready to exploit the opportunities presented by Analytics since maturity and flexibility are missing (Oliveira et al., 2012; Srinivasan and Swink, 2018). In summary, organizations require guidance for managerial actions for Analytics in LSCM before they can exploit the quantitative methods.

1.1.2 Practical Motivation

For the practical motivation, reports from organizations (e.g., technology and Analytics providers, service providers and associations in LSCM, consultancies) have been considered, which infer the effects of Analytics on LSCM from their own projects or larger samples. Discussed below are the extracted aspects of gains in efficiency, customer orientation, business potential, and reluctance. These aspects strongly relate to the theoretical aspects displayed above but present the perspectives and communications from practitioners.

The practitioners' perception, expectations and actual **gains in efficiency** are similar to the theoretically argued performance effects. Analytics has been reported to gain strategic priority due to improved decision-making abilities from increased visibility, even though the monetary return is unclear (Johnson and Cole, 2016; Thieullent et al., 2016). Thereby, organization-wide strategies to exploit Analytics are indicated to be more efficient with leaders in LSCM expecting higher returns than followers (Pearson et al., 2014; Schmidt et al., 2015). This concurs with the research results emphasizing the need for process maturity to gain benefits from Analytics in LSCM. The reported gains from Analytics in LSCM are usually discussed related to applications. A frequently used example is predictive maintenance of machines and transportation assets, which achieves benefits like less failures and higher availability, and results in higher yield, higher utilization and subsequently reduced cost (Lueth et al., 2016; Monahan et al., 2017; Opher et al., 2016; Thieullent et al., 2016). Real-time visibility of assets and process conditions is repeatedly emphasized for achieved asset control and utilization from dynamic adjustments on new information ("real-time optimization") as well as fast reactions on incidents, both avoiding cost (Henke et al., 2016; Jeske et al., 2013; Pearson et al., 2014; Thieullent et al., 2016; UPS, 2016). Further specifically named applications are demand forecasting (with increased accuracy), which avoids cost of committing too much or too few resources, and systematic analysis of expenses, which allows improved control of expenses (Henke et al., 2016; Jeske et al., 2013; Johnson and Cole, 2016; Phillipps and Davenport, 2013). Additionally reported improvements are shortened time of processes, optimized resource consumption, identification of issues and their root cause, improved process quality and performance, removal of unnecessary process steps, and optimization of processes along the supply chain, all eventually resulting in cost savings (Erwin et al., 2016; Henke et al., 2016; Jeske et al., 2013; Johnson and Cole, 2016; Opher et al., 2016;

Thieullent et al., 2016). The expectations from organizations planning to adopt SCA, are similar to these reported benefits (Henke et al., 2016; Kersten et al., 2017; Thieullent et al., 2016). In summary, reports show a similar impact of SCA as scientific research.

Considering the review above, the reported and theorized benefits are principally internally focused on operations and show little effect on the customer. However, Analytics is also reported as a critical mean for **customer orientation** in LSCM. Research has mentioned the customer briefly as an eventual beneficiary, since monitoring of suppliers and service providers becomes easier and resulting in the fulfillment of customer requirements (Sanders, 2016; Wang et al., 2016). Further, it becomes possible to perceive customer needs and behavior in more detail, and act more customer oriented, which has been stated as key argument for investments in Analytics (Kache and Seuring, 2017; Ramanathan et al., 2017; Sanders, 2016). Practitioners' reports address this aspect from several perspectives. One such effect being increased customer satisfaction from avoided product shortages, is mentioned repeatedly (Jeske et al., 2013; Thieullent et al., 2016). Further, Analytics in LSCM has been explained as necessary to cope with changes in customer behavior and requirements based on Business-to-Customer trends and the digital transformation. These changes lead to increased expectations in customization of products and services, immediacy and convenience, which result in higher demand uncertainty (Monahan et al., 2017; Opher et al., 2016; Thieullent et al., 2016; UPS, 2016). Business-to-Business sector customers are expected to demand similar data and Analytics-driven services as they observe in Business-to-Customer sectors like tracking and tracing, but also transparency and comparability of cost and quality, and full-service offerings (Dichter et al., 2018; Garner and Kirkwood, 2017). Additionally, Analytics is argued as a critical driver for improved understand of customer needs, the context of their needs, and reasons for their satisfaction or dissatisfaction (Dichter et al., 2018; Jeske et al., 2013). Based on Analytics, internally executed customer segmentation and externally offered data-driven services are drivers to address customers more individualized and oriented on their identified needs (Jeske et al., 2013; Kersten et al., 2017).

The previous aspect already indicates how business of LSCM is changing, but the **business potential** from SCA is far greater. The business potential from Analytics in LSCM is highlighted by organizations perceiving it favorably to use LSCM as starting business area for Analytics in the organization due to promising returns, a source of untapped efficiency and continuous improvement, and a mean to create reliable orchestration of supply chains without the need of full control (Jeske et al., 2013; Kiron et al., 2012; Lavalle et al., 2011; Opher et al., 2016). However, this paragraph shall highlight the relevance for data-driven business models and digital services in LSCM due to new forms of collaboration and innovation enabling new revenue streams (Jeske et al., 2013; Kersten et al., 2017; Straube, Bahnsen, et al., 2017). Business models are impacted by Analytics in three different ways: (1) upgrading existing services and products by incorporating Analytics into them, (2) changing the business model due to new possible actions enabled by Analytics, and (3) creating new Analytics-driven business models (Lueth et al., 2016). Upgrading the existing business models can result from enhancing products and services with data and Analytics-driven features that add value to the customer such as end-to-end track and trace ("visibility"), or end-to-end booking (Dichter et al., 2018; Lueth et al., 2016). An example of changing the business model in LSCM based on Analytics would be crowd-based last mile solutions, which depend on analysis of real-time data streams on demand and available supply in the crowd (Jeske et al., 2013). The reports further present examples between upgrade and change of business models, taking and redesigning existing services such as brokerage and forwarding with Analytics to prove better service quality, automation for increased efficiency, and advanced abilities to identify opportunities for customers (Dichter et al., 2018; Monahan et al., 2017). However, these opportunities are under threat from technology-savvy organizations, which might deploy Analytics-driven innovations faster and shape customer expectations while attacking profitable processes and might be preferred by shippers due to the savings opportunities (Dichter et al., 2018; Garner and Kirkwood, 2017). Finally, an example for new business models for LSCM is the monetization of data including offerings to completely new partners. Data can be collected with Internet-of-Things (IoT) devices attached to distributed and moving assets in the network or is already collected to execute global operations (Dichter et al., 2018; Jeske et al., 2013). Thus, revenue may be generated from data on climate, pollution, traffic, origin and destination pairs, which can be of interest to governmental agencies, economic analysts, insurances or banks.

In line with the barriers discussed in the theoretical motivation, but in contrast to the potential value of Analytics for LSCM, practitioner reports show **reluctance** in adopting Analytics to LSCM, which, like barriers, leads to missed benefits of analytics. Scientific research has briefly indicated missing adoption and investments (Brinch et al., 2018; Schoenherr and Speier-Pero, 2015). But the presented picture in practitioners' reports is more dramatic. These reports present multiple areas where organizations in LSCM struggle with Analytics or with creating a conducive environment to adopt Analytics, since organizations experience challenges in collaboration, workforce, cost and data (APICS, 2015; Kersten et al., 2017; Pearson et al., 2014; Thieullent et al., 2016). Some organizations adopting Analytics do not realize the aspired success due to the barriers or missing commitment (Thieullent et al., 2016). However, some organizations also see no priority to invest in Analytics. A variety of reports (LSCM specific surveys and cross-industry comparisons) identify LSCM as a "laggard" in Analytics with 50% to less than 10% of organizations reported to have implemented some form of Analytics (Erwin et al., 2016; Kersten et al., 2017; Pearson et al., 2014; Thieullent et al., 2016). Taking a deeper look, UPS presents implementation spanning over several levels of maturity with few organizations achieving the highest levels and warns about a widening gap with latecomers at risk of becoming disadvantaged in competition (UPS, 2016). In addition, LSCM is below average in creating value from Analytics in cross-industry comparison, is ranked lowest as thought leader in business function comparison and about 40% of respondents in a LSCM survey don't plan to invest (Bange et al., 2015; Erwin et al., 2016; Kersten et al., 2017). Germany is especially highlighted for investing heavily in hardware under the industry 4.0 movement while not investing in Analytics in a comparable manner which creates a risky imbalance (Thieullent et al., 2016). Today's high degree of excellence in LSCM has been achieved without Analytics and the sector takes pride in it, but there is a limit for these methods, which Analytics can overcome (UPS, 2016). Analytics has currently no priority for many organizations in LSCM, with some organizations expecting it to become critical within 5 years and others never (Johnson and Cole, 2016; Lueth et al., 2016; Pearson et al., 2014; Schmidt et al., 2015). But, as mentioned above, shippers increasingly rely on Analytics-driven technologically savvy organizations, which absorb some profitable services of traditional LSCM organizations and "it seems there's a disconnect between what shippers and [Logistics Service Providers] believe will happen" (Johnson and Cole, 2016, p. 12).

1.1.3 Summary Motivation

As illustrated in Figure 1, reviewing the scientific literature and practitioners' reports has presented an extensive range of advantages and values that can be gained from adopting and employing Analytics in LSCM. While the advantages primarily revolve around improvements of processes to increase efficiency, increase utilization, reduce times, and

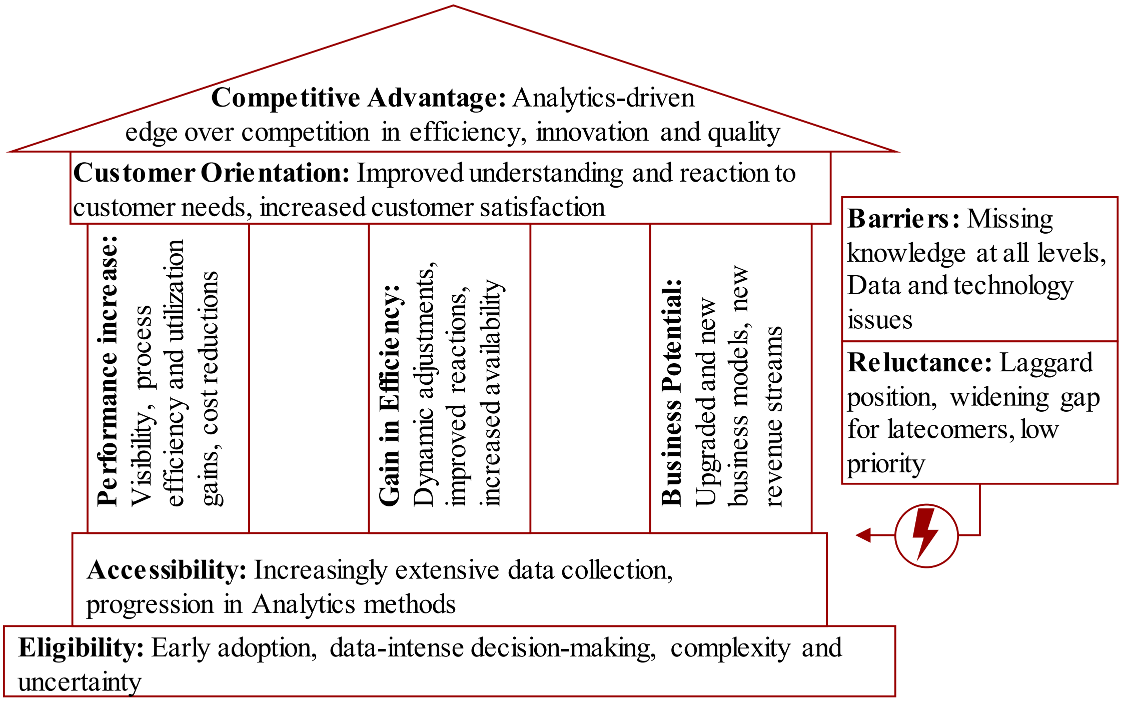

Figure 1: Summary of research motivation

improve quality, they are widely expected to reduce costs as indirect effect due to the process improvements. These have been interpreted as drivers of competitive advantage in scientific literature and competition-crucial in practitioners-oriented publications. The expectations and early adopter examples report improved customer orientation and newly created business opportunities.

However, the review also highlighted several issues to achieve these aspired benefits. A multitude of challenges are reported for using SCA, which are hardly connected to analytical methods but instead to the creation of an organizational and technological environment to make the use of Analytics possible. Further, some organizations in LSCM are unable to recognize how or which benefits can be achieved and need guidance for Analytics. Building maturity in Analytics is essential for these organizations to compete in an increasingly digitalized market. This market will see further market entries from organizations without a background in LSCM but eager to exploit opportunities based on tools such as Analytics and determined to gain market share with it. Currently, LSCM organizations already compete with IT organizations employing digital business models and may experience even more competition, if IT organizations start to provide physical processes with autonomous vehicles as well (Ludwig, 2017; Straube, Bahnsen, et al., 2017). The issues that need to be addressed and solved by this thesis are therefore managerial issues of guiding organizations to a mature state to execute SCA.

1.2 Research Objective

As presented in the previous section, major struggles for organizations in LSCM and managing LSCM activities – from here on "*LSCM organizations*" – with Analytics are managerial and this thesis intends to provide guidance to overcome them. To form an appropriate research design to address these struggles, this thesis assumes a managerial approach, adopted from strategic management, to create specific research objectives, develop directions for the thesis and gain structure. Hence, this thesis follows the five-stage strategy execution process (SEP) as presented by Gamble et al. (2015). Besides structure, the SEP provides an overall coherence to this research and a practitioner-oriented terminology for the research process, which fits the application-oriented nature of this thesis. The following list provides the adaptation of the SEP of Gamble et al. (2015) to this thesis:

- Stage 1: Developing a strategic vision, mission and values [of the thesis]
- Stage 2: Setting objectives [for the scientific articles compiling the thesis]
- Stage 3: Crafting a strategy to achieve the objectives [by creating research designs for the scientific articles] and move the [thesis] along the intended path
- Stage 4: Executing the strategy [by conducting the research]
- Stage 5: Evaluating and analyzing the external environment and the [research's] internal situation to identify corrective adjustments

Starting with Stage 1 of the SEP, the vision is supposed to describe course and direction (Gamble et al., 2015). Explicitly, the vision of the thesis is:

> *LSCM organizations are enabled to use Analytics such that it creates a sustainable competitive advantage and continuous improvement of processes and customer satisfaction*.

There are three components to this vision. First, organizations shall be enabled, which addresses their capabilities to use Analytics and to consequently deploy the results into business processes and having an organization wide acceptance for and familiarity with Analytics. The word 'enabled' thereby refers to goal-oriented and deliberated actions when using Analytics and setting up a supporting organizational environment. Second, the effect from using Analytics shall be sustainable competitive advantage. By using Analytics, organizations are supposed to position themselves better in the market by having superior products, services, or value-added services and possessing deeper insight into their market. Third, the internal effect shall be continuous improvement of processes and customer satisfaction for products and services. These examples ought to underline that process improvement can occur in forms perceptible by customers or solely internal, while both can provide value to the focal organization and customers.

From this vision, a mission is derived. The mission describes the present scope and purpose (Gamble et al., 2015), in this case, of the thesis. This mission represents the overall **research objective** of this thesis. Regarding the research motivation (section 1.1), organizations have high expectations towards Analytics but lack the ability to use it in a successful manner, to provide value from it or are not enabled to use it at all. Consequently, the mission/research objective of this thesis, pursued by collecting and analyzing empirical evidence from organizations successfully applying Analytics, is to:

> *Provide guidance that enables LSCM organizations to use Analytics successfully and turn it into sustainable competitive advantage and continuous improvement of processes and customer satisfaction*.

Following the vision, "enable" refers to goal-oriented and deliberated actions and the existence of a supporting organizational environment in LSCM organizations.

To conclude stage 1 of the SEP, values are developed for pursuing the vision and mission statement of this thesis. Due to the activities being of a research nature, the values for this thesis are derived from recommendations for creating influential scientific results (Fawcett et al., 2014). The resulting values for this thesis are as follows:

(1) The divergence from previous research is clearly articulated and the contribution explicitly presented
(2) The research is justified by clearly highlighting the reasoning behind conducted research and shortage in existing research
(3) The research is written with precision to create understanding and persuasion for the results.
(4) The research is grounded in existing theory and uses it appropriately
(5) The methodology and data collection process are explained and justified in detail, transparent and adhere to scientific standards while bias is aimed to be minimized.
(6) Results are tested for validity and reliability.

Subsequently, objectives are set to convert the vision into specific targets in stage 2 of the SEP, whereby objectives represent desired results in the SEP (Gamble et al., 2015). To derive the objectives, this thesis adapts the theory on structuring problems (TSP) from the early AI research, which provides abstract directions for solving a problem (Simon, 1973). According to the TSP, a problem is defined by the following characteristics:

(1) Defined criteria to test proposed solutions
(2) Problem space delineating an initial state, a goal state and all other reachable states
(3) Attainable and legal state changes in the problem space
(4) Knowledge about the problem is presented by the problem space
(5) The problem space reflects the behavior of the external world
(6) Processes of state changes require a practical amount of activities ("computation") and information for the processes is effectively available

The definitiveness of these characteristic specifies the problem's position on a theoretical continuum between well-structured and ill-structured problems. According to the TSP, the position on the structure continuum determines the ability of a "solver" to solve the problem (Simon, 1973) – since the solver possesses *guidance* to solve the problem. For the purpose of this thesis, the solvers are LSCM managers using the results of this research to solve their problems. Further, their problems are to enable their LSCM organizations to use Analytics in a manner creating sustainable competitive advantage and continuously improving processes and customer satisfaction. Transferring the abstract TSP to this thesis allows **sub research objective** to be derived, which in turn contribute to defining this problem's characteristics and moving it towards being well-structured. Consequentially, four characteristics have been chosen due to their relevance and close relation, as illustrated in Figure 2. The sub research objectives are as follows:

(1) **Definition of the problem space**: Identify the different dimensions, which delineate the states of LSCM organizations adopting and employing Analytics.
(2) **Definition of the initial state**: Describe and characterize the current state of LSCM organizations using Analytics.
(3) **Definition of the solution state**: Describe and characterize how LSCM organizations create sustainable competitive advantage and continuous improvement of processes and customer satisfaction.
(4) **Identification of operators to change states and conditions of their applicability**: Identify operators allowing a path of state changes from the initial state of LSCM organizations using Analytics to the solution state along reachable states in the problem space.

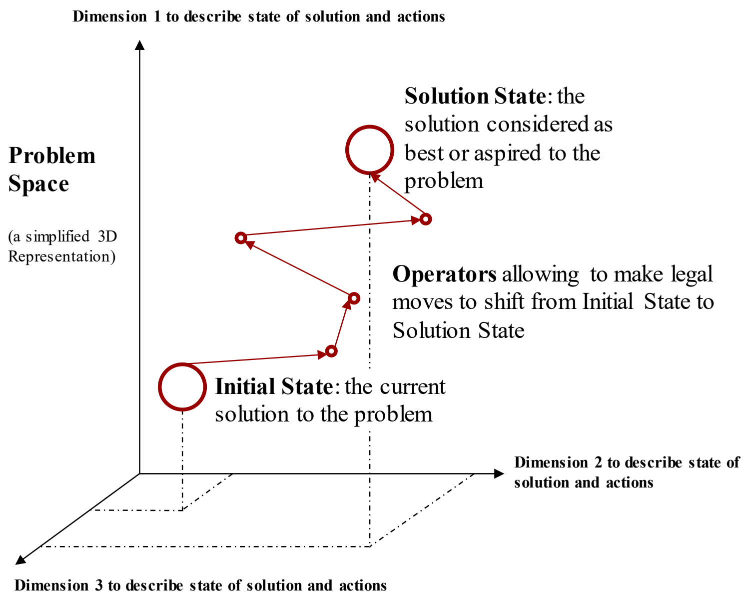

Figure 2: A problem's definition

For the sake of completeness, further characteristics have been formulated, which would be required to be define such that the structure of the problem moves further towards a well-structure (Simon, 1973). First, the differences distinguishing states and tests to detect the presence of these differences need to be defined. Second, connections of operators to the reduction or removal of the specific differences of states need to be established.

The four articles of this cumulative thesis will focus on consecutively addressing each individual objective with specific research questions. As illustrated in Figure 3, the SEP provides further structure to this thesis. Stage 3 of the SEP demands for strategies that address how the objectives are achieved (Gamble et al., 2015), which will be explained in the next section and the motivation for the individual research design of the articles.

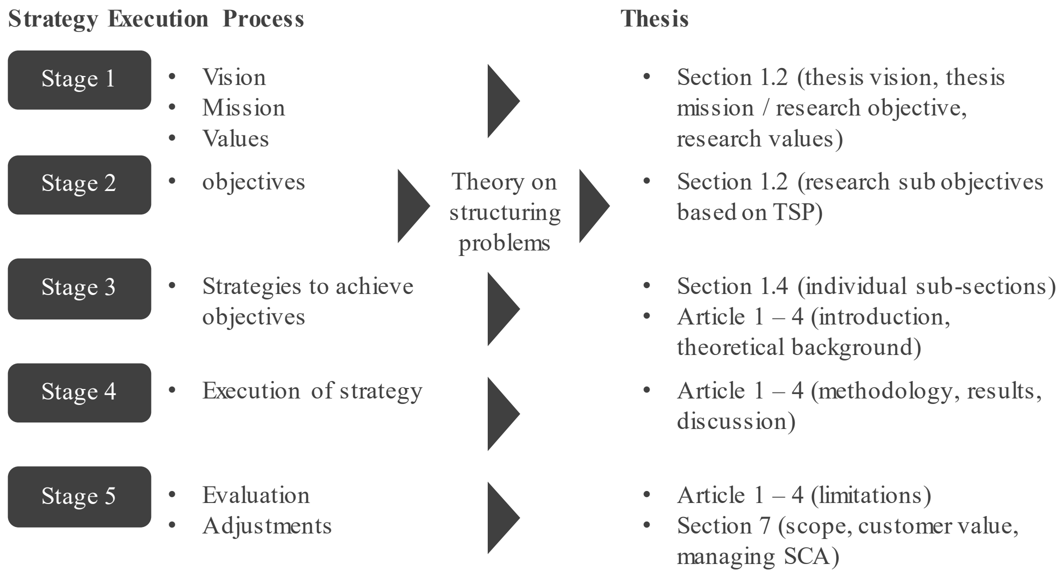

Figure 3: Affiliation of thesis content to SEP

These strategies construct the strategic plan of this research and thus the overall research objective of this thesis. The execution of the strategies (Stage 4) is presented by conducting research in goal-oriented data collection, analysis and interpretation. Finally, evaluating performance and initiating corrective adjustments (Stage 5) corresponds to validation of results of each article and Section 7 of this thesis.

1.3 Unit of analysis

After the research objective, the sub research objectives and their construction have been explained above, the **unit of analysis** must be delineated. This thesis focusses on Analytics initiatives, a special term defined in section 2.2, executed by LSCM organizations. As such, the unit of analysis does neither concern supply chains, organizations or the characteristics of data-driven versions of them. Instead, it concerns processes, their architecture and their management in organizations. Hence, the St. Gallen Management Model (Rüegg-Stürm, 2003) is used to delineate the unit of analysis.

Regarding the processes considered, an Analytics initiative produces infrastructure for business processes in form of Analytics solutions such as customer processes, value creation processes or value innovation processes. The effects on these processes will be discussed but are not in focus of the investigation. Thus, negotiations with customers on analytics services, changes of employee profiles and roles in value creation of new business models are not in focus of this thesis. However, the initiatives creating the Analytics solutions are thus supporting processes. While this thesis investigates these supporting processes, it further investigates their design, control and organizational structure, which represents their management processes as well.

In detail to management processes, normative management has several points of contact to Analytics. The ethical use of data, transparency of employees' actions, adherence to legal regulations on data privacy and security, data governance or the automation of jobs are relevant to the holistic view on Analytics. These topics are investigated for their impact on the execution of Analytics, but since they are not part of the execution itself, no in-depth investigation will be conducted, or designated frameworks designed. In contrast, the strategic management of Analytics initiatives is specifically investigated in this thesis. Thereby, on the one hand the use of Analytics initiatives to create capabilities that provide responsiveness to market signals and improve the competitive position are investigated. On the other hand, the capabilities themselves are investigated in form of initiatives organizations execute. Regarding the operative management, practices are investigated that concern leadership of employees, budget and quality management. However, none of the practices is individually investigated in detail. Rather an overview of practices relevant to the execution of Analytics initiatives shall be created. In the sense of providing *guidance* to execute Analytics initiatives, this thesis focusses on providing well founded directions and options, which are represented by the possible capabilities, creation of these capabilities, and practices to improve the capability creation process. However, the thesis does not assume any context of Analytics initiatives beyond the application in LSCM. Detailed investigations of capabilities or practices in a particular context would allow individual procedures to be developed in relation to the capabilities and practices in that context, but the author interprets this as going beyond the principle of *guidance*, which has been declared as research objective.

Concerning the support processes, Analytics initiatives will be investigated regarding the sub processes listed by Rüegg-Stürm (2003) including human resources, education, infrastructure management, information management, communication, and risk mitigation. However, like explained for management processes, the investigation of Analytics initiatives concerns *guidance* for their execution. Thus, the investigation is intended to identify a variety of superior practices regarding these sub processes that present a range of options to choose from, and derive a rationale for the tasks' superiority, since this is interpreted as *guidance* for this thesis. Investigating the practices of these sub processes in different contexts to develop individual procedures is, again, not in focus. Hence, developing specific Analytics solutions or recommending and categorizing analytical methods and problems as well as assessing, developing or recommending technologies is likewise not in focus of this thesis.

In accordance to the St. Gallen Management Model (Rüegg-Stürm, 2003), further elements influence the processes and, thus, the execution of Analytics initiatives, which have to be understood for their effect to provide *guidance*. Hence, ordering moments of strategy, structure and culture regarding Analytics are in focus for their effect on the execution of Analytics initiatives including favoring and obstructing designs of them, and the rationale of the effect. Their creation is not focus of this research, such that the creation and implementation of a data-driven strategy or data-driven culture is not investigated. Ordering moments not specifically concerning Analytics beyond the restriction to LSCM is also not in focus. Analytics initiatives are understood in this thesis to support atomic business processes of an LSCM nature (e.g., deliver, transport, store, order, allocate, schedule, replenish) without concerning the organizational structure the business processes are executed in (e.g., manufacturing, retail, or logistics services organization). These atomic business processes are assumed to induce similar problems to be solved in Analytics initiatives despite the organizational structure. Furthermore, interaction topics, stakeholders and environmental spheres similarly comprise the potential to influence the execution of Analytics initiatives. These aspects of the St. Gallen Management Model will be collected for their influence and relevance. They will be investigated in regard to their relevance, such that customers (users) and employees (analysts) will be investigated in more detail as compared to for example non-governmental organizations.

1.4 Structure

The structure of this thesis is created to consecutively advance in the definition of the problem – as described by Simon (1973) – of how to enable organizations to manage SCA. Thus, six structural elements emerge: Introduction and theoretical background, the four individual research inquiries, and guidance to manage SCA. Subsequently, this thesis ends with a conclusion, limitations and implications for research and management.

1.4.1 Introduction and theoretical background

The introduction of this thesis explains the theoretical and practical research motivation. Thus, aggregated aspects from respectively scientific literature and organizational reports are presented. These argue for the necessity of research and appraise the impact of it. In addition, the introduction explains the overall research objective of this thesis and outlines how the individual research questions of the scientific articles compiling the thesis relate to that overall research question. Furthermore, the unit of analysis is described.

The theoretical background introduces relevant terms and background related to LSCM and Analytics. For that purpose, definitions and relevant related terms are considered. Further, to substantiate the domain specific research on Analytics limited to the domain of LSCM, the use of Analytics in different domains is briefly reviewed.

1.4.2 Article 1: Mapping Domain characteristics influencing Analytics initiatives

The first objective of defining the problem space is an exploratory task into different factors, which might affect the outcome of adopting and employing Analytics in LSCM. Thereby, for the purpose of this research, using Analytics refers to the execution of initiatives, which are either discoveries leading up to a major decision with changes in executing LSCM activities based on the results, or to a data product (or Analytics

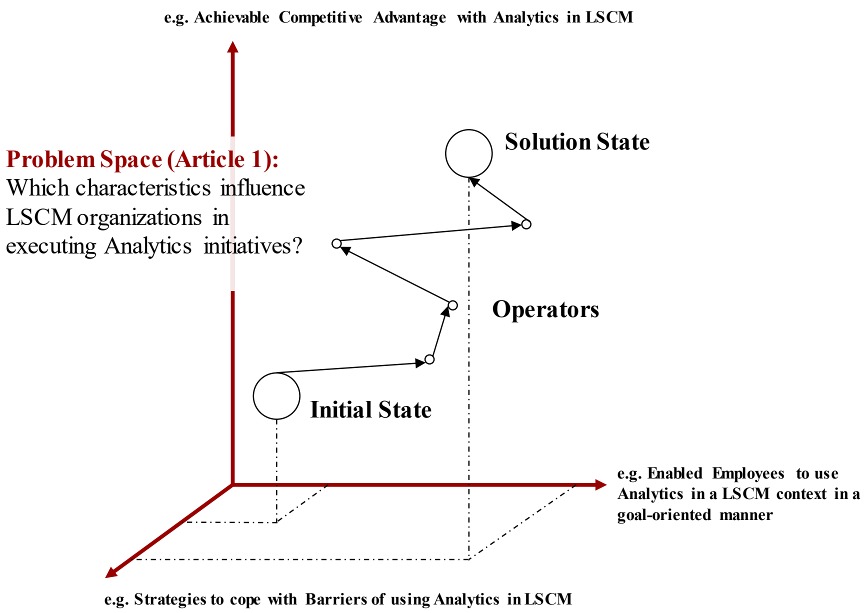

Figure 4: Focus of article 1

product), which is supposed to be used continuously in a process. The outcome of adopting and employing Analytics in LSCM is thus describing the outcome of an Analytics initiative. Therefore, this outcome does not refer to the accuracy or optimality of analytical methods or other evaluation criteria of that sort. Instead, the considered outcome of the Analytics initiative is the achieved (continuous) decision support, fulfillment of relevant requirements for providing support, and the fit of these requirements to the decisions to be made. Further, relevant considerations of the outcome of initiatives are, whether results are complete, are deployable, are used by decision makers, and are providing their desired functionality according to the requirements until their retirement. As illustrated in Figure 4 in accordance to the TSP, this spans a space of multiple dimensions, allowing the description of an initiative's or organization's state. However, not all dimensions may be relevant or decisive at all instances.

To achieve the desired problem space, an exploratory research method will be used, which relies on the collection of empirical evidence. To explore this space, factors will be inquired, that distinguish Analytics initiatives. To create a relation to the domain within the focus of this thesis and create an executable research design, these factors will be derived from an inquiry into characteristics that set Analytics initiatives in LSCM apart from initiatives in other domains.

1.4.3 Article 2: Archetypes of Supply Chain Analytics

The objective of describing the current state of Analytics in LSCM likewise demands exploration. Thus, Analytics initiatives in LSCM are explored and aggregated to create

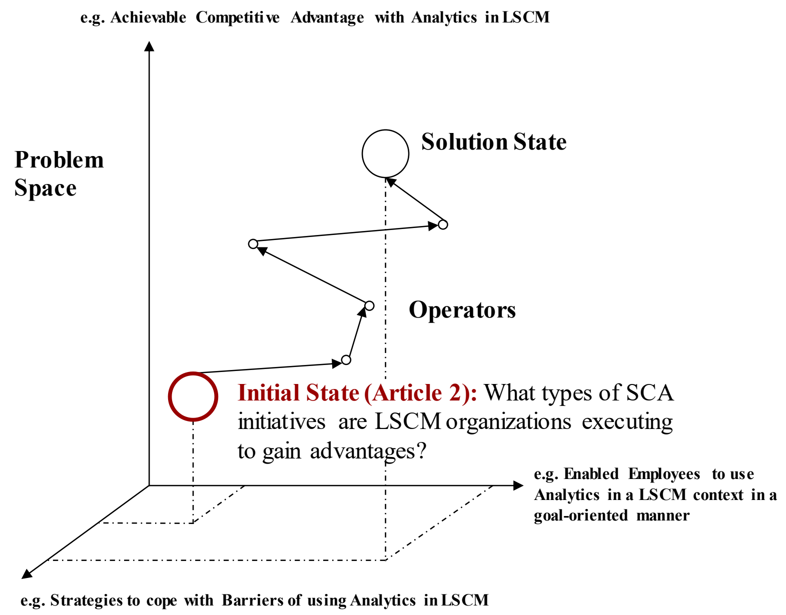

Figure 5: Focus of article 2

an overview and more comprehensible insight into Analytics in LSCM. The fit into the overall research objective regarding the TSP is displayed in Figure 5.

To execute this exploration, Analytics initiatives in LSCM are collected with the focus on goals, as well as resources, and means to achieve these goals. Thus, the data collected will diverge from problem space characteristics of article 1, reasoned as follows. First, the research inquiry individually displays relevant and interesting insights. Second, the research design is executable, since goals, resources and means are more accessible for observation as compared to the various dimensions. Third, the intended research results are catered to the audience of this research – managers in LSCM – who can use them as inspiration to create own initiatives. Thus, based on the collected data, the Analytics initiatives will be clustered – aggregated based on patterns in the characteristics – and interpreted for their cluster internal commonalities to derive Archetypes. This presents one perspective, but not a holistic view, of the current state of Analytics in LSCM.

1.4.4 Article 3: Explaining the Competitive Advantage Generated from Analytics with the Knowledge-based View

The third objective addresses the description of the solution state. While the previous objectives are exploratory in nature, the third objective is supposed to provide a confident and evident guidance for managers in which direction to develop their Analytics activities. Thus, this guidance needs to provide reason – confirmation – that the solution state is the best state to aspire towards. Exploration is not intended to provide this reasoning and this inquiry needs to go beyond exploration. Thus, explanatory research

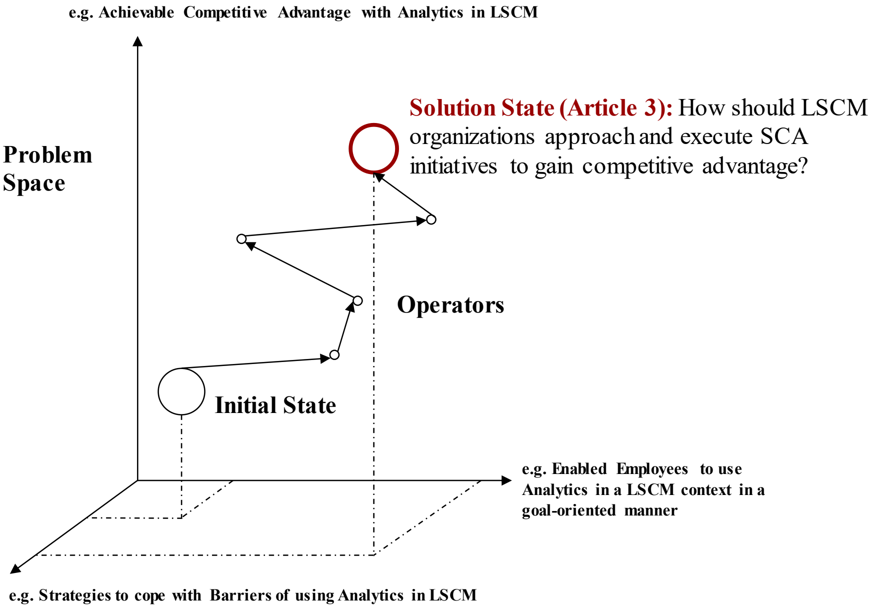

Figure 6: Focus of article 3

with confirmatory research methods are needed to address this research inquiry. The fit of this objective into the TSP is illustrated in Figure 6.

To provide a description of the solution state, the actions taken in Analytics initiatives of LSCM organizations successfully applying Analytics will be aligned and compared to a theoretical argumentation for competitive advantage. In more detail, the actions of LSCM organization executing Analytics initiatives will be aligned and compared to the knowledge-based view (KBV). Thereby, the considered actions certainly include analytical actions. However, in accordance to the vision of this thesis, non-analytical actions – specifically management actions – are considered, which include management of resources, teams, and tasks. Thus, the actions and the explained intentions behind these actions within the empirically collected data will be compared to the reasoning of the KBV, which describes why competitive advantage emerges from knowledge, while implying Analytics to increase knowledge. This allows for actions leading to valuable and beneficial Analytics initiatives to be provided with reasoning for their effect.

1.4.5 Article 4: Overcoming Barriers in Supply Chain Analytics

Fourth, operators to change state in the problem space according to the TSP are intended to be identified. Transferring the abstract objective into a research design, this inquiry intends to identify barriers and challenges in adopting and employing Analytics, since these barriers are interpreted as obstacles for state changes towards the solution state. Thus, overcoming barriers would allow to change states as illustrated in Figure 7. To overcome barriers, measures need to be identified and evaluated for their impact. Thus,

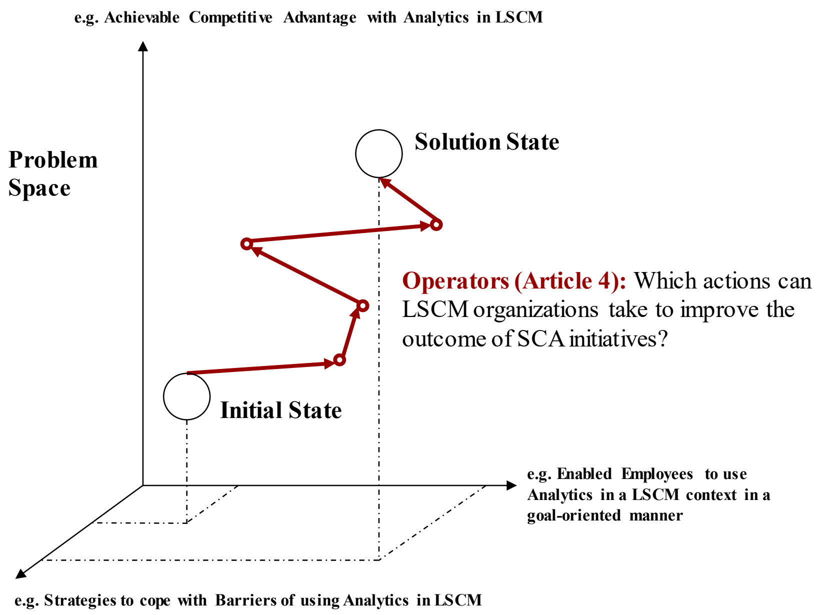

Figure 7: Focus of article 4

this research inquiry is exploratory for the most relevant barriers and measures and intends to derive core themes in measures that help to overcome the barriers and successfully execute Analytics initiatives in LSCM organizations.

To achieve this objective, this article's research design takes a mixed methods approach, which allows for exploration and condensation of data to derive core categories. The research design intends to identify the operators, assess their impact and gather further insight on the context in which the operators can be applied. This research inquiry will focus on barriers and challenges in Supply Chain Analytics and will limit the collection of empirical data to that domain.

1.4.6 Managing Supply Chain Analytics

Finally, the findings of the four individual articles are used to create guidance for managers in LSCM to manage their Analytics initiatives in two approaches. First, the collected data and insights are accumulated into a discussion on the direct and indirect value for customers created from Analytics applied in LSCM. This discussion presents a variety of exemplified use cases and how they provide value. Second, a well-established process model for Analytics is supplemented with the data and insights collected for this thesis to provide *guidance* for managing distinct SCA initiatives. In further detail, preceding the supplement of an Analytics process model with the collected data and insights for the inquiries, 14 process models of Analytics are reviewed to converge terms in Analytics process models and put them into context of a 15th process model – the Cross-industry standard process for data mining (CRISP-DM). The CRISP-DM process model

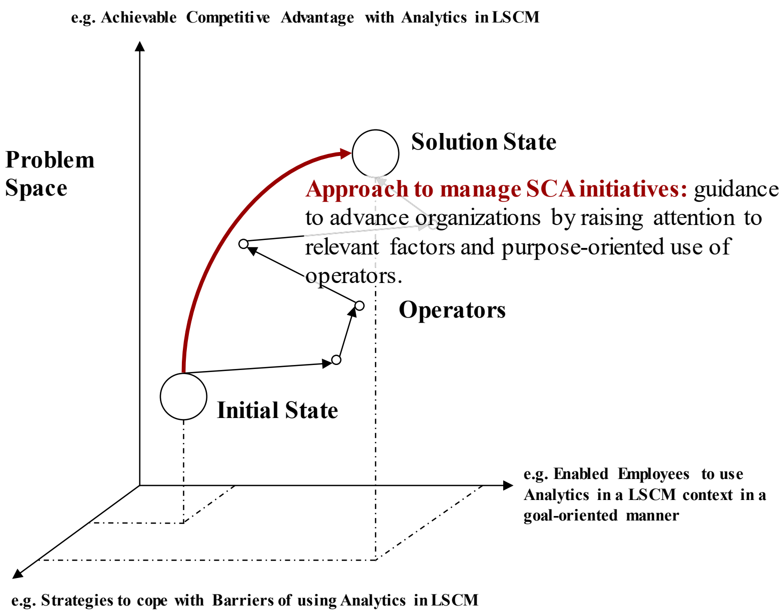

Figure 8: Intended goal of aggregating and enriching the articles

is the most widely used process model in Analytics. Subsequent to the alignment of terms and process steps, it will be enriched by the insights from the four research inquiries. This process model provides a tool for managers to plan and execute Analytics initiatives beneficially with anticipation of and resilience to eventual challenges.

The provided *guidance* is intended for managers in LSCM aspiring to execute Analytics initiatives and supposed to enable them to apply Analytics in LSCM with sustainable competitive advantage and continuous improvement of processes and customer satisfaction. Thus, the provided guidance enables them to manage SCA. The fit to the overall objective is illustrated in Figure 8.

2 Theoretic Background

This section introduces the leading terms of this thesis. First, Logistics and Supply Chain Management are defined and the treatment of both terms as one for this thesis is argued. Second, Analytics is explained and the relationship to the terms Big Data, Data Science and Artificial Intelligence is described. Third, Supply Chain Analytics, the intersection of Logistics and Supply Chain Management with Logistics is portrayed together with other subfields of Analytics to illustrate the unique characteristics of it.

2.1 Logistics and Supply Chain Management

The core of this thesis is the part of Analytics that is referred to as Domain (Davenport et al., 2010). The Domain is the field of application that is in focus of Analytics to create improvements or insight. The design of this thesis intends to enable these improvements and insight in the domain of Logistics and Supply Chain Management with the purpose to contribute to the scientific literature and practical execution of Analytics in this domain.

2.1.1 Logistics

The term Logistics has been defined in various ways. Pfohl (2010) categorized definitions in lifecycle oriented, service oriented and flow oriented. The latter is notably more specific about subject and tasks and will be considered in more detail. The subject of Logistics is material flows from the initial supplier to the final customer and related information flows, which have to be planned, controlled, executed and monitored (Straube, 2004). These flows are necessary since the materials must transform in time and space to get from time and location of suppliers to the time and location of consumption by the customer (Pfohl, 2010). The focus of the material flow in relation to a focal organization has led to create several subfields of Logistics including procurement Logistics, distribution Logistics, site Logistics or disposal Logistics (Gudehus, 2012). These differ in the specific activities, but the high-level tasks of planning, controlling, execution and monitoring are relevant for all of them.

As indicated in the definitions above, to accomplish logistical tasks, the lines of business units and organizations have to be crossed. Baumgarten (1980) explained the thought of Logistics being a discipline mastering material flows inside and outside of the own organization in physical, informational and organizational regards in the beginning of the 1980s. While he does so in the prologue of the book and while todays ‘holistic’ view of

Logistics concerning the flows across organizations is already envisioned in the substance of his book, which represents the state-of-the-art of Logistics at the time, the rest of the book addresses matters of internal material flow. In practical application, cross organizational logistics networks were widely established in the 1990s (Straube, 2004). The holistic way of thinking about Logistics, a core concept in the Logistics literature (Baumgarten and Walter, 2001; Kopfer and Bierwirth, 2003; Pfohl, 2010; Straube, 2004) that has been introduced as early as 1974 (Pfohl, 1974), manifests the concept of interdisciplinary and interorganizational management of material flows by promoting to understand logistics networks as systems orienting their actions on customers' demands and needs, no matter whether the system entails several organizations or is distributed globally. This way of thinking demands instruments of exchanging information (Straube, 2004).

2.1.2 Supply Chain Management

The second term of relevance, Supply Chain Management, has similarly to Logistics no uniformly accepted definition. Reoccurring elements in leading Supply Chain Management literature are integrated and collaborating organizations, established relationships between these organizations, and approaches leveraging the relationships to organize business activities of these organizations and flows of assets, products, information and funds such that products are produced and delivered to the customer efficiently and with minimal costs (Bowersox et al., 2007; Chopra and Meindl, 2016; Christopher, 2011; Hugos, 2011; Simchi-Levi et al., 2003). The collaborating organizations are supposed to be all organizations upstream from the customer, which are necessary for designing, making, distributing and using products (and services) such as suppliers, manufacturers, warehouses, and stores (Hugos, 2011; Simchi-Levi et al., 2003). Their collaboration is supposed to increase the surplus of the supply chain such that all supply chain members benefit (Chopra and Meindl, 2016) and the customer value is superior (Christopher, 2011). This perspective is sometimes similarly to Logistics literature labeled as 'holistic' (Christopher, 2011; Hugos, 2011; Simchi-Levi et al., 2003).

The term Supply Chain Management was introduced by consultants of Booze Allen Hamilton in the beginning of the 1980s as a result of several projects in logistics. The concept is supposed to differ from classical material flow and manufacturing concepts in a variety of aspects. According to Oliver and Webber (1982), the supply chain is recognized as single entity including the several business functions involved in the material flow in an organization. It represents strategic decision-making, since the functionality of the supply chain becomes a shared objective. Further, inventory is considered as balancing mechanic and, finally, the supply chain should ultimately be considered as an integrated system and not as conjunctions via interfaces. However, the article of Oliver and Webber (1982) does not introduce the concept as replacement, opposition or subordinate to Logistics. It rather describes it as completing the concept of logistics. By considering supply chain management as novel approach to Logistics, their conception can be interpreted as uplifting the function of Logistics, which was underrecognized for strategic purpose to this point, or incorporating a Logistics focus into strategic decision-making.

2.1.3 Synopsis

While the previous introductions present two parallel existing terms with resembling objectives, focus and requirements of interorganizational thinking, which seemingly were not intended to exist in conflict or competition, a dispute about the terms relationship to each other has developed. The dispute goes so far that the relationship of these terms has been the subject of research. Larson and Halldorsson (2004) develop four different perspectives about how the two terms are related. With their research based on a survey of educators, they show the existence of different perspectives of the relationship of the two terms and some aspects being more likely to be associated with one or the other term. However, their research does not show any value in the existence of two terms. The aspects they use to distinguish the terms, which are practices, methods and tasks, are all eventually relevant for organizations with non-simple material flows. Rather, an implication of their research is that the two terms for the same thing but with differently understood relationship increases the complexity between organizations to align, communicate and achieve optimal performance of the Logistics system or Supply Chain. Consequently, having two terms might be a barrier to achieve either term’s objective of the Logistics system or Supply Chain acting as a system for increased efficiency, reduced cost and, most importantly, superior customer value.

Concluding, while there remains to be a controversy about the relationship between Logistics on the one hand and Supply Chain Management on the other, the discourse about this relationship does not seem to provide any value. Both claim to focus on executing the operational, tactical and strategical actions to ensure provision of goods and services with the goals of appropriate effectiveness, efficiency, quality and sustainability under holistic thinking concerning interdisciplinary and interorganizational perspectives. Value is, as argued by the author of this thesis, provided in science for organizations by developing insights and means to improve the executed actions towards their goals – improve effectiveness, efficiency, quality and sustainability and guide to holistic thinking – and not by arguing about how to label a field. Thus, for the remainder of this thesis, the two terms are treated as equal and fairly labeled as Logistics and Supply Chain Management (LSCM). Regarding this thesis' focus on process, as the **working definition of LSCM**, it is comprised of the processes that enable the flow of materials and related assets, information and funds from the initial supplier to the final customer by actions of planning, controlling, executing and monitoring. Holistic thinking, efficiency and cost minimization are understood as quality criteria for LSCM, but not necessarily as part of the definition.

2.2 Analytics and related terms

As one of the interviewees in the research designs presented below mentioned "terms describing the field [of Analytics] change faster than the actual methods". In this thesis, to consider the phenomenon of data analysis for decision-making as will be explained below, the term Analytics has been chosen as central term. The term is more explicitly associated with management issues, and the author of this thesis perceives Analytics as start for an essential wave of data analysis for decision-making in organizations leading it to be widespread today and during the conduct of this thesis's research. Further, the term Analytics is perceived by the author as most stable, while press, public attention and conversations on other terms left an impression of hype-inflated and unsubstantiated expectations. In this section, Analytics is defined and put in relation to the terms Big Data, Data Science and Artificial Intelligence by highlighting differences and similarities. In addition, following common phrasing in literature using the terms Analytics initiative or Data initiative for describing goal-oriented Analytics activities, this thesis will use the term Analytics initiative as well (Davenport and Harris, 2007; Holsapple et al., 2014; Marchand and Peppard, 2013; Ransbotham et al., 2016). Especially reflecting LaValle et al. (2010), as **working definition of Analytics initiatives**, it comprises all actions over the full life-cycle of an Analytics solution that contribute to its sustainable impact and continuity, including the determination of the objectives with Analytics, the execution of analytical activities, the development of Analytics solutions, the deployment of Analytics solutions, and their active and regular maintenance and performance preservation.

2.2.1 Analytics

There is a variety of definitions and explanations for Analytics. Davenport and Harris (2007), who initiated the broader recognition of Analytics with their famous book “Competing on Analytics”, describe Analytics as “extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions”. This description is focused on activities, which include management in addition to the use of analytical methods and makes the purpose of decision-making and subsequent actions immanent – the idea of Analytics not being done for the purpose of Analytics is made part of the description. This idea was made central to a meta definition Holsapple et al. (2014) have derived from considering several definitions, which is recognized as the **working definition of Analytics** for this thesis. They describe Analytics as being concerned with “evidence-based problem recognition and solving that happen within the context of business situations”. Thereby, evidence-based is supposed to emphasize that decision-making from Analytics is not (just) based on data or facts, but also on justified estimates, well-reasoned approximations, or credible explanations.

A common way to subcategorize Analytics is the distinction of Descriptive Analytics, Predictive Analytics and Prescriptive Analytics (Bedeley et al., 2018; Cao and Duan, 2017; Davenport, 2013; Holsapple et al., 2014; Ransbotham et al., 2015). Descriptive Analytics is described as the backward looking form of Analytics, identifying trends, describing context and providing aggregations, which are evident from the data and can be reported from it (Bedeley et al., 2018; Cao and Duan, 2017; Davenport, 2013). In some cases, Descriptive Analytics is also explained to look for causes and “why” things happened (Ransbotham et al., 2015; Spiess et al., 2014). Predictive Analytics is focused on estimating and forecasting future events or behavior based on models that consider what happened in the past (Bedeley et al., 2018; Davenport, 2013; Ransbotham et al., 2015). Thus, the basic assumption is that patterns in the data will sustain. Finally, Prescriptive Analytics is providing guidance by assessing the best – ‘optimal’ – actions regarding different scenarios of future events and behavior (Bedeley et al., 2018; Ransbotham et al., 2015). While this could be easily compared to the field of Operations Research, Prescriptive Analytics is opposingly supposed to be integrated and employed in business processes requiring the creation of solutions in close collaboration with experts from other areas, the adoption of a wide scope, the integration of problems, and the flexibility of solution, what makes Operations Research a field Analytics leverages from as one of several components (Liberatore and Luo, 2010; Phillipps and Davenport, 2013).

A focus that is repeatedly addressed in the literature concerning the term Analytics is managerial issues. Providing means to managers to set up the organizations to gain the aspired value from Analytics and enabling organizations to deploy Analytics is the core topic of Davenport and Harris (2007). The execution of initiatives, operationalization and influencing factors on value generation have been addressed including factors which can omit the realization of the value after analytical methods have been conducted such as communication and consumability of the results (LaValle et al., 2010; Ransbotham et al., 2015; Seddon et al., 2017; Wedel and Kannan, 2016; Wixom et al., 2013). Thereby, the focus diverges from the analytical methods to the broader integration of the methods' results into the value creation process. Further managerial issues that have been addressed are organizational culture and skill gaps, including the skill gaps of managers that need to be filled, the fit of Analytics into the structure of an organization and the application areas of Analytics in organizations (Acito and Khatri, 2014; Beer, 2018; Marchand and Peppard, 2013).

2.2.2 Big Data

The second term of interest, Big Data, can be traced back to an article describing necessary developments in data management principles to keep pace with requirements to harness the information from organizational activities, especially in e-commerce (Laney, 2001). To support businesses, IT organizations were demanded to implement data management architectures which can handle an increasing data volume, the velocity data is created and the variety of formats that must be collected. At that point, the three 'V's' focused on backend technologies to enable analytical approaches but not on the analytical part. As a simple way to describe Big Data, the V's were carried on and expanded, especially in scientific literature, to lists somewhere between three and ten V's (Brinch et al., 2018; Sivarajah et al., 2017; Tsai et al., 2015; Wang and Alexander, 2015). This more recent characterization of Big Data expands the focus beyond data management and architectures to the exploitation of data by analytical means. However, scholars repeatedly comment on Big Data as concept and field of research to be not well established and the impact of the V's to be imprecise (Brinch et al., 2018; Gandomi and Haider, 2015; Sivarajah et al., 2017). It was further emphasized that the exploitation of value from Big Data requires Analytics (Carillo, 2017; Gandomi and Haider, 2015; Troester, 2012). In this regard, the terms Big Data and Big Data Analytics are used synonymous to Analytics (Akter et al., 2016; Debortoli et al., 2014; Hopkins and Hawking, 2018), as it is understood in this thesis.

The characteristics of data emphasized with the Big Data term change the analytical approaches to store and analyzing data, since processing is more challenging, has to happen in short time for larger and more complex streams of data and has to handle different and incomplete types of data (Tsai et al., 2015). Commonly associated with Big Data are forms of distributed processing, which distributes the workload of storing and analyzing data across different machines to be handled in parallel (Philip Chen and Zhang, 2014). Different forms are specialized for different purpose such as batch processing, like the quite famous Hadoop, or for stream processing, like Splunk or Apache Kafka. Analytics Solutions that require such distributed processing usually display a high degree of technical complexity as presented by Markl et al. (2013).

2.2.3 Data Science

Data Science is the third term of interest. While the term exists for a longer time, larger popularity can be traced back to an article about Data Scientists, describing it as the "sexiest job of the 21st century" (Davenport and Patil, 2012). The term describes an advanced type of analysts, who can handle large amounts of data, can code, employ advanced quantitative techniques and can communicate the results in understandable manner, often with a background in a scientific field that uses complex quantitative methods (e.g., a PhD in physics, social science or ecology). However, the article backfired and created an ambiguous term that could mean almost anything and is applied to a variety of jobs, frustrating the authors and leaving the Data Science field similarly undefined (Davenport, 2014a). Several scholars have provided a short summary or definition for Data Science. Dhar (2013) describes it as "the study of the generalizable extraction of knowledge from data" and in the discussion that follows, describes a focus on more complex analytical and quantitative methods as well as on decision-making, primarily automated. O'Neil and Schutt (2013) present an extensive discussion about the ambiguity of the term and eventually present Data Science as the activities executed by data scientists, which are the extraction of meaning and interpretation of data with a variety of analytical methods and integrating a variety of skills. The Essential Knowledge series of the MIT Press, defines it as "encompassing a set of principles, problem definitions, algorithms, and processes for extracting nonobvious and useful patterns from large data sets" in the book on Data Science (Kelleher and Tierney, 2018). In the considered literature, the emphasis is usually on 'extraction' of insight from data with few attentions to subsequently creating value from the insights. Concerning the relation of Data Science and Analytics, the terms are used synonymous for insight extraction from data with the difference that Data Science comprises more complex methods but less focus on practicality in business (Larson and Chang, 2016; Marchand and Peppard, 2013; Viaene, 2013).

The Data Scientists are the focal point of the discussion about Data Science. In the discussion on the Data Scientists, it is agreed that they execute the analytical tasks. Apart from that, their responsibility and capability is argued between having a large variety of skills and executing the larger part of initiatives (Debortoli et al., 2014; Dhar, 2013; Grossman and Siegel, 2014) and them taking a limited role in initiatives and working with a team that contributes complemental skills and capabilities, argued with strong rejection of an omnipotent Data Scientist (Carillo, 2017; Viaene, 2013; Vidgen et al., 2017). Whatever their role is, Data Scientists are explained to need a sense for Business (Davenport, 2013; Marchand and Peppard, 2013). They are further described to use more advanced methods, such as machine learning and skills for using Big Data, which are traditionally not taught in statistics courses (Dhar, 2013; Larson and Chang, 2016; McAfee and Brynjolfsson, 2012). But "just" hiring Data Scientists is not the guarantee to create value from data (Carillo, 2017; Marchand and Peppard, 2013).

2.2.4 Artificial Intelligence

Fourth and final, AI is another term currently used in context of creating value from data. The scientific field of AI has a long history with a primary focus on the challenge of creating intelligence for machines, with the creation of solutions for business as second order. Russell and Norvig (2016), and Boden (2016) display a variety of definitions and approaches to define AI and discuss the ambiguity about expectations in the field. Summarizing their considerations, an AI is a virtual machine that is dependent on a physical machine, whereby AI is understood as their combination either as computer, a program on a computer or an Agent, which is a certain program that can operate autonomously, perceive its environment, persists over time, adapts to changes and creates and pursues goals. The capabilities that display intelligence are further under discussion. While capabilities of visions, reasoning, language, learning and further are usually used to describe intelligence, the necessity of displaying human-like understanding and grasping of the meaning of these capabilities for being an AI is seen differently. Boden (2016) explains the visionary goal of the field to be the creation of an “Artificial General Intelligence” with this human-like capacity. Since there is still no full understanding of what human intelligence is and how it works, this is estimated to be unachievable by some scholars in the field of AI.

In a business context, achieving intelligence is rarely in scope. Rather the capabilities – typically labeled as “tools” – and the techniques to achieve them are in focus in a business context (Akerkar, 2019). The techniques are distinguished in knowledge-based systems and machine learning. The knowledge-based system/expert systems are based on programmed rules by experts the AI has to follow, which brought a first wave of industrial applications of AI in the end of the 1970s and beginning of the 80s but failed to deliver on their ambitious goals (Alpaydin, 2016; Russell and Norvig, 2016). Machine learning extracts these rules from data – learns from data/trains on data – by using mathematical techniques such as Bayesian probabilities and neural networks, dominating the current attention and progress in AI (Akerkar, 2019; Alpaydin, 2016; Boden, 2016; Russell and Norvig, 2016). Deep learning is a sub form of machine learning originating from more complex neural networks, technically named deep neural networks for their model structure. Especially the techniques of machine learning, now usable due to technological advances, are argued to provide advanced opportunities as analytical methods to exploit value from data (Beer, 2018; Davenport, 2013; Vidgen et al., 2017). However, the use of AI in organization has a wider scope than analytical issues. From a generic perspective, AI is distinguished in three forms (Rao, 2016). First, Assisted AI, which simplifies and accelerates tasks while humans make the decisions. Second, Augmented AI provides extensive input for the humans’ decisions and resultingly shares decision rights. Third, in the Autonomous AI case, the machine acts and decides autonomously. Davenport and Ronanki (2018) took a use case perspective of AI employed by organizations and distinguish in one use case group of Analytics – referring to it as “Analytics on steroids” – and other groups of automating repetitive processes and communication tasks. Thus, Analytics is one area which is empowered by methods from AI (Akerkar, 2019; Gandomi and Haider, 2015; Philip Chen and Zhang, 2014).

2.2.5 Synopsis

In summary, the literature behind these terms above similarly describes the concept of exploiting data for better decision-making. However, the focal points of this exploitation differ. Big Data tends to focus on technological aspects along with opportunities to exploit data with characteristics that require these technologies. The focus of Data Science is on execution of the ever more powerful methods and the resulting opportunities of exploiting insights from data. The machine learning techniques and methods provided by AI focus on learning from data, which provides advanced opportunities for analytical issues but is only one of several usages of AI, what would make the use of the term AI misleading for this thesis. Finally, management aspects, execution of initiatives, the organizational objectives of analytical approaches and other aspects of implementing the methods in organizations are in focus of Analytics. For this research, the practical and scientific insights associated with all terms are relevant. However, for the reason of the management focus associated with the term Analytics and the further reasons explained in the introduction to this section, Analytics is used as central and comprehensive term in this thesis.

2.3 Analytics in different Domains

In this section a deeper look will be taken into current research in a variety of domain-specific Analytics to illustrate the differences of Analytics in different domains. For this purpose, different data-rich domains have been chosen, which encounter different challenges (LSCM, Marketing and healthcare), one that seems trailing behind (public sector) and, at last, one field that is seemingly different to traditional organizational processes, to show similarities in using Analytics (Sports).

2.3.1 Supply Chain Analytics

LSCM is suitable to use Analytics, as it is a data-driven and data rich environment and is seen as an early adopter of quantitative Methods from Operations Research (Chae, Olson, et al., 2014; Souza, 2014). The use is driven by the overall objective of matching supply with demand, since demand may not be postponed and the supply is perishable, as usual for service industries (Souza, 2014). In addition, supply and demand become increasingly uncertain due to fast changing customer expectations, process variations, inconsistent suppliers, and ever-increasing networks (Chae, Olson, et al., 2014; Kache and Seuring, 2017; Wang et al., 2016). The objective of matching is accompanied with a multitude of objectives pursued with Analytics in the literature, which are basically the objectives

LSCM pursues anyway. Popular are the objectives of reducing costs, increasing efficiency and effectiveness, and increasing customer orientation, while further objectives are improving quality, reducing time/increasing agility and flexibility (Chavez et al., 2017; Kache and Seuring, 2017; Schoenherr and Speier-Pero, 2015; Souza, 2014; Wang et al., 2016). Subsequently, the benefits organizations aspire to achieve with Analytics to meet these objectives are of better integration with supply chain partners and improved planning input (Kache and Seuring, 2017; Wang et al., 2016). However, the most notable emphasized benefit aspired, which might not require the most complex methods but can be technologically and organizationally challenging, is visibility (or transparency). Visibility is stressed to contribute to the objectives above by improved capabilities to handle variability, uncertainty, environmental influences, market conditions, supplier and customer needs, and sudden problems, by assessment of progress to achieving goals and need for adjustments, by determining compliance of suppliers to quality and regulations, by gaining insights on supply chain wide inventories and activities, by detecting the need for corrections of poor performance to ultimately make better and faster decisions, especially in real time. (Chavez et al., 2017; Kache and Seuring, 2017; Sanders, 2016; Wang et al., 2016).

Due to the scope of LSCM, the Analytics applications are countless. Along different time frames and different organizational levels, organizations created applications on the demand side (e.g., as planning input) for demand forecasting, analyzing purchasing patterns, and product assortment optimization. On the supply side applications have been created for supplier segmentation, supplier selection, supplier evaluation, risk detection, risk management, definition of auction mechanisms, design of negotiation strategies, and analysis of spend profiles. Further, distribution and manufacturing applications include location optimization/network design, scheduling, segmentation of routes, vehicle routing, forecasting of estimated-time-of-arrival (ETA), predictive maintenance, capacity planning, reduction of shrink, reduction of material waste, labor scheduling, labor efficiency optimization, optimization of fuel efficiency, optimization of driver behavior, material requirements planning, master production planning, support product design and identification of bottlenecks (Chae, Olson, et al., 2014; Sanders, 2016; Souza, 2014; Waller and Fawcett, 2013; Wang et al., 2016). These applications are fueled by internal data from ERP and other Systems and the transactions, static data captured and Analytics results, which go into other applications, as well as increasingly the data from several dispersed entities of the supply chain like suppliers, carriers and points of sale including inventories, cost, process times, demand and their forecasts (Souza, 2014; Wang et al., 2016). Larger data volumes and more precise data become available due to sensor technology like RFID, GPS or IoT capturing temperature, light intensity and vibration, which are used in the supply chain (Kache and Seuring, 2017; Sanders, 2016).

However, this multiplicity of applications, data and data sources comes at a price. Organizations suffer from fragmented efforts without systemization and coordination. This makes the aspiration of organization and supply chain wide objectives extremely challenging and defies the benefits achieved (Sanders, 2016). A study on cloud logistics has emphasized that logistical objects and resources lack standardized categorization and ontology including their informational representation (Glöckner et al., 2017), which magnifies the issue. Further challenges highlighted for LSCM are the cost of Analytics, the unwillingness of partners to share information, what hinders supply chain wide approaches, and the complexity especially of optimization problems (Sanders, 2016; Schoenherr and Speier-Pero, 2015; Wang et al., 2016). Further, rather common barriers are reported as well including lack of experienced personnel, data security issues, lack of integration of systems, change management issues, lack of data for the applications intended and abundance of data without applications determined (Kache and Seuring, 2017; Sanders, 2016; Schoenherr and Speier-Pero, 2015).

2.3.2 Marketing Analytics

Marketing is a historically data-rich domain, which started professional data collection with organizations like Nielsen in the 1920s and advanced data analysis as early as the 1960s (Wedel and Kannan, 2016). The use of Analytics in Marketing aims at harnessing the customer for better decision-making (Germann et al., 2013), with two overall objectives: personalization and effective resource allocation. Detailed data about the customer and analysis of the data enables personalized marketing which leads to the growth of more profitable customers with better customer relationships (Leeflang et al., 2014; Rust and Huang, 2014; Wedel and Kannan, 2016). This contrasts the mass market centered and transaction driven marketing, and eventually displays a paradigm change to the customer as profit center with opportunities for additional sales (Leeflang et al., 2014; Rust and Huang, 2014). Personalization aspires even to address contextual needs, e.g., based on the customers position (Rust and Huang, 2014; Wedel and Kannan, 2016). Even though personalization has become less resource demanding, complete personalization might not display the best use of resources (Wedel and Kannan, 2016), leading to the second objective of resource allocation. More detailed knowledge about the customer, or his customer journey, enables to direct resources to more profitable customers and limits resources to others (Leeflang et al., 2014; Rust and Huang, 2014; Zhao, 2013). The benefits for Marketing from Analytics are improved decisions due to more decision consistency, exploration of broader decisions, abilities to assess the relative impact of decision variables and more granular decision-making by exploiting customers' heterogeneity and needs, which they provide voluntarily by communication or unknowingly by online behavior (Germann et al., 2013; Rust and Huang, 2014; Wedel and Kannan, 2016). Thereby, the impact of Analytics on Marketing positively depends on competition strength and frequency of customer preference changes (Germann et al., 2013; Leeflang et al., 2014).

Analytics applications in Marketing are either decision supportive or decision automating (Germann et al., 2013). This includes segmentation for personalized Marketing via Email, estimation for click-through rates for automated bidding on online advertisement space, survival analysis for churn prediction, lead scoring and several predictive techniques for direct-marketing opportunities like next best offer, cross selling/up selling campaigns or win-back campaigns (Leeflang et al., 2014; Leventhal, 2015; Zhao, 2013). However, the estimation of the customer lifetime value with Analytics stands out (Rust and Huang, 2014; Wedel and Kannan, 2016; Zhao, 2013) . The data enabling these applications are now coming from all sorts of data producing sources: smartphones, smart TVs, internet clickstreams and click-through behavior, blogs, tweets, or other social media-based customer content and interactions (e.g., videos, comments, likes), or the purchase history with marketing eventually knowing more about customers than their friends (Leeflang et al., 2014; Rust and Huang, 2014; Wedel and Kannan, 2016; Zhao, 2013). The value in these data comes from the possibility to observe customers of competitors instead of solely observing the own customers (Wedel and Kannan, 2016).

Challenges are privacy issues from all the data flood (Wedel and Kannan, 2016) and usually very low accuracy for future predictions, despite all the data (Leventhal, 2015). Further, with the growth of data and the various Marketing channels, the question for accountability of the different Marketing measures increases (Leeflang et al., 2014). This leads to subsequent challenges, since mass Marketing will still be necessary as Marketing channel and an organization must track and account for various channels and touching points of customers with advertisements and spillovers across channels (Leventhal, 2015; Wedel and Kannan, 2016). The emphasis on accountability and data heavy decision-making in Marketing is further argued to slow down decisions as well as hindering creativity and innovations and thus reduce Marketing performance overall (the so-called “data-innovation dilemma”) (Germann et al., 2013; Leeflang et al., 2014).

2.3.3 Healthcare Analytics

Healthcare is another data rich environment, but these data are usually stored as hardcopy and get increasingly digitalized opening the opportunities for Analytics (Raghupathi and Raghupathi, 2014). Thereby, a variety of actors is interested in the Analytics enabled potential of these data including physicians, patients, policy makers, insurances and the general public (Shneiderman et al., 2013; Srinivasan and Arunasalam, 2013). Due to the different actors, a multitude of objectives has evolved. An overall objective is to improve health of patients and quality of healthcare (Kohn et al., 2014; Shneiderman et al., 2013). Considering the different actors, sub-objectives are to enable participation of patients in decision-making and care for their health, personalizing treatment accounting for individual patient characteristics, creating access to healthcare, keeping the health system economically sustainable (e.g., preventing fraud), directing the knowledge growth of healthcare to guide decision-making, improving allocation of resources including medical specialists, and optimization of the care process (Belle et al., 2015; Kohn et al., 2014; Raghupathi and Raghupathi, 2014; Shneiderman et al., 2013; Srinivasan and Arunasalam, 2013). All these objectives are accompanied by the aspired reduction of costs (Raghupathi and Raghupathi, 2014; Shneiderman et al., 2013).

Resulting, a variety of applications using healthcare data exists including assessment of national health status or trends (e.g., obesity or spreads of diseases), improved alert systems for critical patient conditions, prediction of critical conditions, pattern recognition in drug interactions, predictions of treatment or healthcare habit to adjust the respective (Kohn et al., 2014; Shneiderman et al., 2013), and genomics, which is supposed to deliver the necessary insight for personalized care and treatment development for complex diseases (Belle et al., 2015). The data comes from a magnitude of point-of-care data sources including clinical sensors, images, electronics health records or written notes (Kohn et al., 2014; Shneiderman et al., 2013). However, increasingly external sources create relevant data for Healthcare Analytics including personal sensors, social media, pharmacies, or laboratories (Raghupathi and Raghupathi, 2014; Shneiderman et al., 2013).

Yet, the data is a major challenge for healthcare Analytics. First, there is a magnitude of data types such as different imaging techniques, physiological signals or textual records. Second, coming from different devices, data exist in different data formats, images have different resolutions or dimensions, and signals must be geospatially and temporally aligned and are highly context dependent (Belle et al., 2015; Shneiderman et al., 2013). Third, data is frequently stored in siloed systems with inefficient sharing at care providers or in personal devices preventing a holistic view of a patient's medical condition (Belle et al., 2015; Kohn et al., 2014). Fourth, using this data raises privacy issues (Viceconti et al., 2015). Fifth, even with all issues resolved, there is still variability in the target variables since humans differ, complicating the creation of accurate and robust models. However, highly accurate models are needed because the costs of an error are very high since they influence potentially lifesaving decision (Raghupathi and Raghupathi, 2014; Srinivasan and Arunasalam, 2013).

2.3.4 Public Sector Analytics

Governments and agencies historically store data for several reasons including legal reporting or administrative usage (Fredriksson et al., 2017), while they provide a myriad of applications and services: tax, health, defense, public safety and national security, social services, transportation, disaster management, agriculture, energy, government finance, fire and police services, education or waste collection (Daniell et al., 2016; Gamage, 2016; Malomo and Sena, 2017). However, with this range comes decentralization with a resulting immature state of progression in Analytics (Daniell et al., 2016; Desouza and Jacob, 2017; Gamage, 2016; Malomo and Sena, 2017).

Due to its fundamental task, a major objective of applying Analytics is a more efficient allocation of public resources. Analytics-based, this might be achieved by understanding current needs and preferences to direct resources to the most needed areas as well as predicting future needs, acting proactively and designing prevention measures (Daniell et al., 2016; Fredriksson et al., 2017; Malomo and Sena, 2017). This is accompanied by the objectives of cost reduction of public services (Gamage, 2016; Malomo and Sena, 2017) and increased transparency of public decision-making (Fredriksson et al., 2017; Klievink et al., 2017) with subsequent increased involvement in and acceptance of policies by citizens (Daniell et al., 2016).

Consequently from the variety of services, there is a multitude of example applications: route optimization for waste collection, transparency initiatives about commissioned services, optimized infrastructure expansions, resource allocation after environmental or humanitarian disasters, improvement of ambulance fleet dispatch, pattern recognition for city inspector allocation (Daniell et al., 2016; Desouza and Jacob, 2017; Malomo and Sena, 2017). However, these examples are limited in range and usually bound to local authorities with rare spillover to other cities. Further, some authorities create digital channels for service delivery with little known generated benefits (Malomo and Sena, 2017). While data in the public sector is usually structured and static with missing granularity for Analytics, increasingly real-time sensor and camera data are used to monitor traffic or identify needed infrastructure investments (Gamage, 2016; Malomo and Sena, 2017). In addition, the use of social media data has been attempted but has revealed several issues including the unequal access of socioeconomic groups to digital communication technologies (Desouza and Jacob, 2017).

The public sector is facing a variety of challenges which are disruptive to many Analytics initiatives. Data access across different authorities is a major challenge due to their siloed organizations resulting in different IT systems and infrastructure, with different standards (or rather a lack of standards across authorities), and different methodologies of data collection (Desouza and Jacob, 2017; Malomo and Sena, 2017). Further, there are uncertainties amongst authorities of what can legally be shared since rules are inaccurate and concerns of breaching privacy regulations and consequent loss of trust are high, as well as, in case of commissioned services, agreements about data sharing might even be missing (Gamage, 2016; Malomo and Sena, 2017). This is magnified due to unsolved questions of privacy about personal data raising ethical concerns about using and sharing of data (Malomo and Sena, 2017) and in some cases the prohibition of public organizations to perform tasks outside their statutory tasks since they are funded for respective tasks (Klievink et al., 2017). If all these issues would be resolved, the public sector still experiences a skill gap since the private sector can pay higher salaries (Gamage, 2016). And even if this gap could be overcome, the general operating principal of the public sector would complicate the use of Analytics, since decisions are made for society at large, the policy making is driven by a non-monetary public value and this public value is dependent on the political value system of the elected representatives, which might be driven by short (or rather shortsighted) time horizons with reelections in mind (Daniell et al., 2016). Efficient or effective resource allocation thus becomes vague. Overall, the public sector has a high degree of uncertainty about where and how to use Analytics (Klievink et al., 2017).

2.3.5 Sports Analytics

Sports is a field craving for quantified data (Hutchins, 2016) and most professional Sports teams nowadays use Analytics, including the use for on-field decisions (Davenport, 2014b). Sports is seemingly different from other domains, since Sports are usually limited in time, space with rules for behavior, a predetermined objective and, in many Sports, very intense interactions between opposing individuals and teams, which thus compete on the field while cooperating in leagues which might even share revenues (Gudmundsson and Horton, 2017; Stein et al., 2017; Troilo et al., 2016). In terms of markets, Sports and their professional teams compete with other forms of entertainment (Miller, 2015), resulting in Sports being quite similar to other conventional industries with stakeholders demanding the creation of value (Caya and Bourdon, 2016).

The objectives of using Analytics vary with the stakeholder level. In professional Sports, competitors are organized in leagues and federations which strive to attract and retain fans and sponsors (Caya and Bourdon, 2016; Miller, 2015). The team stakeholders like managers and coaches are interested in increasing revenues and financial performance from selling tickets and merchandise as well as to improve their performance in the respective Sport by developing tactics, player preparation, evaluation and recruitment or identifying weaknesses of opposing teams (Caya and Bourdon, 2016; Stein et al., 2017; Troilo et al., 2016). The individual athletes desire – in self-service or with specialists – to improve their athletic performance by enhancing understanding of on-field performance, training, diets, general health and injury prevention (Caya and Bourdon, 2016; Davenport, 2014b).

Consequently, different stakeholders demand various applications. To engage fans, entertainment products are created from data, Analytics and metrics (Caya and Bourdon, 2016). To increase revenue, dynamic pricing or sponsorship measurements are performed (Caya and Bourdon, 2016; Troilo et al., 2016). Coaches want to explore, which tactics and lineups work. They do so by identifying promising on-field positions for actions, by classifying styles of athletes and their most likely behaviors, by understanding patterns in successful and unsuccessful attacks, or by assessing the importance of players to teams (Davenport, 2014b; Gudmundsson and Horton, 2017; Stein et al., 2017). Athletes and coaches are interested in performance metrics of competitions and trainings reflecting productivity and effectiveness of players, which are constantly advanced to include the context of players performance. This context might include the presence or absence of team members (plus/minus analysis), difficulties of performed actions including distance to goal or proximity of opponents, weather changing field position or athletes' stamina (Davenport, 2014b; Gudmundsson and Horton, 2017; Stein et al., 2017). The applications are possible due to optical tracking with cameras from TV providers or many installed in stadia as well as device tracking with wearable devices collecting location and movement GPS-based as well as biometric data. These trackers provide trajectory data which can be combined with, often manually collected, event data to enable advanced Analytics (Davenport, 2014b; Gudmundsson and Horton, 2017; Stein et al., 2017).

The resulting demand for analytical talent and budget usually leads to professional sports organizations cooperating with third-party vendors (Caya and Bourdon, 2016; Davenport, 2014b). The financial power for such invests and the potential benefits is concentrated to the very popular men sports and leaves behind lower level professional sports, semi-professional sports, most women sports and amateurs, eventually creating a digital divide (Hutchins, 2016). It further requires an open mindset and a positive reception towards usefulness from coaches and athletes not always available in "old-line coaches" (Caya and Bourdon, 2016; Davenport, 2014b). In addition, applications often have only a niche of user because of differences in Sports (Caya and Bourdon, 2016; Gudmundsson and Horton, 2017). However, while the specific applications might not be copied from one sport to another, the idea and concept of an application might be transferred and adapted to another sport. Likewise, ideas and concepts of applications of one domain could be transferred to other domains, such as the investigation of plus/minus patterns in treatments could provide input to healthcare or the context-based analysis of delivery vehicles in different delivery areas could provide insights to LSCM.

3 Mapping domain characteristics influencing Analytics initiatives - The example of Supply Chain Analytics

Purpose: Analytics research is increasingly divided by the domains Analytics is applied to. Literature offers little understanding whether aspects such as success factors, barriers and management of Analytics must be investigated domain-specific, while the execution of Analytics initiatives is similar across domains and similar issues occur. This article investigates characteristics of the execution of Analytics initiatives that are distinct in domains and can guide future research collaboration and focus. The research was conducted on the example of Logistics and Supply Chain Management and the respective domain-specific Analytics subfield of Supply Chain Analytics. The field of Logistics and Supply Chain Management has been recognized as early adopter of Analytics but has retracted to a midfield position comparing different domains.

Design/methodology/approach: This research uses Grounded Theory based on 12 semi-structured Interviews creating a map of domain characteristics based of the paradigm scheme of Strauss and Corbin.

Findings: A total of 34 characteristics of Analytics initiatives that distinguish domains in the execution of initiatives were identified, which are mapped and explained. As a blueprint for further research, the domain-specifics of Logistics and Supply Chain Management are presented and discussed.

Originality/value: The results of this research stimulates cross domain research on Analytics issues and prompt research on the identified characteristics with broader understanding of the impact on Analytics initiatives. The also describe the status-quo of Analytics. Further, results help managers control the environment of initiatives and design more successful initiatives.

3.1 Introduction

Analytics has been praised to have a tremendous impact on the world economy by changing the basics of competition and providing leading organizations with an edge in operations improvements and new business models (Henke et al., 2016). This has attracted professionals and researchers alike, creating a variety of domain-specific subfields of Analytics. However, researchers usually do not work across domains

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(Holsapple et al., 2014), while they usually not explain how the specific characteristics of their domain alter the use of Analytics.

One of these subfields is Supply Chain Analytics (SCA) (Chae, Olson, et al., 2014; Sanders, 2016; Souza, 2014) or SCM Data Science (Waller and Fawcett, 2013), which concerns the application of Analytics in Logistics and Supply Chain Management (LSCM). Scholars offer little explanation about differences of executing Analytics initiatives in LSCM as compared to other domains. While scholars investigate the effects of Analytics on LSCM (Chae, Olson, et al., 2014; Chavez et al., 2017), they do not elaborate on the domain-specific execution of Analytics initiatives. Meanwhile, LSCM research demands education programs for data scientists designated to LSCM (Waller and Fawcett, 2013), but while LSCM theory may help analysts to understand the context, benefits to the understanding of a specific practical problem are unknown. In addition, scholars demand training of personnel in the LSCM domain in Analytics as well (Schoenherr and Speier-Pero, 2015), while Analytics research argues for the benefits of domain independent analysts collaborating with domain experts such as in cross functional-teams instead of creating designated analysts (Bose, 2009; Harris and Craig, 2011; Lavalle et al., 2011). Scholars present opportunities and challenges of Analytics in LSCM (Kache and Seuring, 2017; Sanders, 2016), while opportunities do not impact LSCM processes and challenges are not described for their domain specifics. Further, scholars have not presented research on challenges being domain-specific or cross domain.

It is not the purpose of this research to call the advantages of domain-specific research on Analytics into question. Domain-specific research is advantageous for addressing use cases from a domain. It is argued to be more meaningful and have increased impact of Analytics solutions, due to incorporated domain knowledge (Waller and Fawcett, 2013). However, goal-oriented exchange between domains with similar issues may create benefits in spillovers, as it does in collaborating business units in organizations (Grossman and Siegel, 2014). Collaboration across domains on domain-independent issues can provide benefits due to improved understanding of the issues and broader solution search and direct domain-specific research towards issues critically demanding domain knowledge. However, there is no good basis for distinction such as characteristics of Analytics initiatives displaying potentially differentiating effects and issues in different domains. Mapping these characteristics entails the potential to explain maturity and adoption differences in executing Analytics initiatives across the various domains. For instance, while LSCM displays an early adopter of Analytics (Davenport, 2009), this forward-thinking position did not permeate through the field with few organizations keeping up with implementing more advanced approaches (2017) but the field regarded as laggard concerning Analytics (Bange et al., 2015; Thieullent et al., 2016).

Summarized, literature differentiates Analytics by domain with little necessity (Carillo, 2017) besides a more target-oriented addressing of an audience. Domains advance differently in applying Analytics and research lack explanations. A clearer understanding of distinctions can direct domain-specific efforts towards critical domain-specific issues and stimulate cross-domain research and exchange on domain-independent issues. Thus, this research pursues the mapping of characteristics of Analytics initiatives potentially differentiating domains. As such, it follows the call for more investigation of differences of domains in Analytics (Cao et al., 2015). In this effort, this research focuses on the domain of LSCM and the Analytics subfield of SCA. Considering MacInnis (2011), this work contributes by sketching and delimiting SCA. Consequentially, the research question addressed is: *what are characteristics of Analytics initiatives setting domains apart in executing them and which specifications of these characteristics exhibits the domain of LSCM?*

This research concerns the increasing use of data to influence and transform businesses (Carillo, 2017), which is assumed with the label of Analytics. The distinction to terms such as Data Science and Business Intelligence is vague, leading to constant mix by some scholars (Agarwal and Dhar, 2014; Chen et al., 2012; Larson and Chang, 2016; Song and Zhu, 2016). While Data Science is understood as tool for Analytics (2015) and Business Intelligence as technology focused (Larson and Chang, 2016), managerial issues of both are treated as concerning Analytics as well. For the purpose of this research, a distinction based on methods and technologies does not provide any value, while the distinction will be revisited later.

The remainder of the paper is organized as follows: Section 2 provides the theoretical background. Section 3 focuses on the methodology. In section 4 the resulting map of characteristics of Analytics initiatives is presented and discussed. Section 5 concludes this research and provides implications and limitations.

3.2 Theoretical background

In this article, differences between Analytics initiatives resulting from differences relating to the domain are investigated. Thus, this section presents theoretical considerations on the domain, practical impact and the incorporation of domain knowledge into Analytics.

3.2.1 The matter of domain in Analytics

The domain refers to the context (Kenett, 2015), subject field (Holsapple et al., 2014), area (McAfee and Brynjolfsson, 2012) or business function (Bedeley et al., 2018; Carillo, 2017) in which Analytics is applied. Analytics can be applied to a variety of business processes and industries (Davenport and Harris, 2007) and no limitations of domains to use Analytics has been identified. This has resulted in an abundance of domain-specific subfields including Marketing Analytics, Supply Chain Analytics, Financial Analytics and more, while there is little exchange between these subfields (Holsapple et al., 2014).

Scholars consideration of the domain's influence on executing Analytics initiatives is more of a side note. However, the domain is the subject of data analysis and solution deployment and its role in an Analytics initiative is essential considering that the domain and its issues are the overall reason the initiative exists. An initiative does not come out of the void and is supposed to be based on a business need or opportunity of a domain (Grossman and Siegel, 2014; Lavalle et al., 2011; Watson, 2014). The value Analytics can generate by providing solutions and insights is correspondingly related to the domain, in which the insights and models/algorithms are deployed to and applied in (Anant Gupta, 2014; Bedeley et al., 2018; Gupta and George, 2016). This essential link to the domain might be fragile if the domain representatives are not convinced Analytics will meet their needs. Thus, intensive communication, exchange and knowledge integration of analysts and domain representatives is necessary such that the domain will buy-in and the solution deployment is not destined to fail (Dutta and Bose, 2015; Grossman and Siegel, 2014; Wixom et al., 2013). After all, the domain is typically the sponsor of an initiative (Grossman and Siegel, 2014), including the investment of time from domain experts (Viaene and Bunder, 2011).

Besides creating a gateway to purpose, sponsoring and subject of deployment of Analytics solutions, the domains knowledge influences the search for insights. Section 3.2.3 discusses further details on incorporating domain knowledge into an Analytics initiative. This domain knowledge includes among others knowledge about an organizations mission, goals, objectives and strategies, about organizational policies and plans and the understanding of the potential impact of Analytics initiatives on organizational performance. Further, it includes knowledge enabling the interpretation of business problems and appropriate solutions (Ransbotham et al., 2015; Watson, 2014). Scholars argue for the criticality of this knowledge in the success (or rather meaningfulness) of Analytics initiatives (Chen et al., 2012; Debortoli et al., 2014; Harris et al., 2010; Janssen et al., 2017; Wixom et al., 2013).

In detail, domain knowledge provides guidance for the analytical process by determining subsequent steps and a course of action, identifying challenges, giving directions for decision points, and validating results (Ittoo et al., 2016; McAfee and Brynjolfsson, 2012; Ransbotham et al., 2015; Viaene, 2013; Wixom et al., 2013). It enhances the identification of the most valuable opportunities and needs or the best way to apply analytical skills to provide value to the organization (Grossman and Siegel, 2014; Harris et al., 2010; McAfee and Brynjolfsson, 2012). The understanding of the business problem can be improved by domain knowledge, as well as the assumptions behind business ideas and the objective behind applying Analytics (Chiang et al., 2012; Viaene, 2013). Regarding data, domain knowledge leads to choosing the right data and data sources, better understanding of the data as well as potential sources of measurement and collection inaccuracy of the data (Harris et al., 2010; Kenett, 2015). It helps to make sense of results of analyses and patterns found (Debortoli et al., 2014; Richards, 2016) and therefore the creation of more valuable models and solutions and especially to avoid finding insights already known to the domain expert but new to the Analyst (Chiang et al., 2012; Grossman and Siegel, 2014; Harris and Craig, 2011; Viaene, 2013). In relation to this, domain knowledge is indicated to improve Analysts effectiveness and thus the fit of solution to problem (Carillo, 2017; Wixom et al., 2013), Analyst efficiency and Analysts engagement (Harris and Craig, 2011). Finally, domain knowledge improves communication of results (Chiang et al., 2012; Debortoli et al., 2014).

Of course, the domain is not the sole factor indicated to influence Analytics initiatives. Authors have named internal factors including company size (Cao et al., 2015; Davenport et al., 2010), the data-savviness of employees and a data-driven culture (Acito and Khatri, 2014; Carillo, 2017; Gupta and George, 2016; Ransbotham et al., 2016), executive support, prior successes and available expertise (Acito and Khatri, 2014; Ransbotham et al., 2016). Another moderating factor is the fit of Analytics to organizational strategy, structure, and processes (Cao and Duan, 2017). This underlines that one Analytics approach of an organization cannot simply be transferred to another.

3.2.2 The impact of domain on Analytics

A study on Analytics in different business functions shows that some domains are more likely to be supported by Analytics than others. Domains that attract most attention are finance, LSCM, strategy and business development, as well as sales and marketing (Lavalle et al., 2011). These domains are more experienced with statistical and quantitative techniques, are considered historically data-driven, and are expected to have a high payback (Acito and Khatri, 2014; Anant Gupta, 2014; Kiron et al., 2012). This section investigates the impact of domains by considering objectives and challenges.

The objectives of collecting and analyzing data across domains differ and Analytics solutions cannot be transferred from one domain (or organization) to another with the expectation of similar results (Kambatla et al., 2014; Lavalle et al., 2011). This results from domains pursuing different business objectives, working differently and having different issues. Considering different industries, domains differ in regulations, competitiveness, technological change and standards, Analytics standards, time-sensitiveness, or their public importance (Acito and Khatri, 2014; Trieu, 2017). To exemplify, medicine and aviation aim to reduce the cognitive load of the decision maker in highly stressful environments, in which they have high information demands with inadequate time to sort out the most vital information beyond the simple filtering or aggregation (Richards, 2016). In less stressful environments but with requirements for broad oversight and real-time availability, monitoring is pursued by retail and LSCM (Watson, 2014). In contrast, marketing or retail applications target the detection of changes in behavior potentially presenting new opportunities with a completely different time horizon (Shuradze and Wagner, 2016; Trieu, 2017). Another marketing objective of capturing opinions is similarly pursued by politics. But while Marketing requires insights for personalization, political candidates require insights guiding a collective political agenda to all voters (Gandomi and Haider, 2015; Shuradze and Wagner, 2016). Predicting behavior (e.g., demand) is an essential objective in LSCM and utilities but caters subsequent objectives such as optimal resource allocation (Acito and Khatri, 2014; Watson, 2014). Insurances want to gain deeper understanding of why behavioral changes happened to prevent fraud (Watson, 2014). Finally, domains with high frequencies of reoccurring verbal and written interactions, such as tourism, aspire automation of these processes with Analytics (Gandomi and Haider, 2015).

Different domains also bring different challenges for Analytics. Considering the examples below, these challenges result from complexity of conducted analytical methods or from internal and external organizational matters. Challenges closely linked to methods and techniques appear in complex analytical tasks like environmental studies, which demand the combination of spatio-temporal scaled inputs of satellite imagery, weather data and terrestrial monitoring (Kambatla et al., 2014). Domains intending to understand the structure of social networks must control dynamic evolution of connections between entities and dynamic interactions via these connections. Further challenges arise from methods generating large volumes of data output during an analysis requiring storage, like an astro-physical simulation (2014). Additionally, the cost of inaccuracy of the Analytics solutions differs such that false positives (or rather false negatives) of a diseases or fatal condition in healthcare have a different impact as compared to customer preferences in marketing (Kambatla et al., 2014).

Technical challenges can be more frequent and relevant in domains with complex data integration needs. For example, in healthcare data is captured in heterogenic formats and collection is widely distributed over points-of-care (Acito and Khatri, 2014; Kambatla et al., 2014). Further technical challenges from data including data growth, data quality or the degree of unstructured data (Chen et al., 2012; Kambatla et al., 2014), which are, however, hard to connect to certain domain characteristics.

Organizational challenges concern domains working with person-related data. The challenges of securing privacy and subsequent data security are pressing in domains like healthcare, e-commerce or e-government and can trigger ethical issues, which create the need to ethically justify the use of the data (Acito and Khatri, 2014; Chen et al., 2012; Kambatla et al., 2014). Further organizational challenges are the creation of data without any or adequate collection and storage, such as domains that do not store event logs, such as LSCM, or produce loads of handwritten notes with valuable information, such as healthcare (Chen et al., 2012). Special organizational challenges arise in business domains, since the increase of self-service Analytics create the challenge of inadequate knowledge of users leading to subverted effectiveness of the decisions made (Richards, 2016). In addition, business organizations tend to deploy several models and algorithms at once with different data, requirements of speed, different sources of data and data structure, while models, algorithms and their output are not integrated for consistency (Kambatla et al., 2014).

The differences of objectives and challenges across the domains affect various aspects of Analytics. The consideration above suggest that different domains have different requirements for Analytics, have different influence on organizational aspects of Analytics, and integrate Analytics differently into processes (Cao et al., 2015; Davenport et al., 2010; Janssen et al., 2017). Further, domains have different spending on Analytics, while the organizational performance is impacted differently (Cao et al., 2015; Trieu, 2017).

Considering the practical impact of domain characteristics, industry reports give appropriate insight and show substantial differences in the most frequent use cases, adoption rates, main challenges, and data-based business models potentially disruptive in different domains (Henke et al., 2016; Toonen et al., 2016). Striking differences in tendencies for data-driven decision-making as opposed to intuition are reported as well (Erwin et al., 2016). However, reports show similarities in challenges and recurring use cases recur across domains as well (Bange et al., 2017; Toonen et al., 2016).

Concluding, domains differ in objectives and challenges and further show different experiences with Analytics. As indicated, these differences result in and from altered organizational, technical, data related or methodological characteristics.

3.2.3 Modes of incorporating domain knowledge in Analytics initiatives

Two aspects are explored regarding the incorporation of domain knowledge into Analytics initiatives: the domain knowledge holder and the interaction of analysts with the domain.

Considering the knowledge holder, the necessity of analysts to hold domain knowledge and be proficient in numerical disciplines specific to the domain they work in has been argued (Chen et al., 2012; Debortoli et al., 2014; Grossman and Siegel, 2014; Harris and Craig, 2011). Supposedly, this is key to successful analysts able to communicate with the domain representatives. The skills list of the ultimate breed of analysts, the data scientist, usually includes domain knowledge (Carillo, 2017; Debortoli et al., 2014), as part of portraying a jack-of-all-trades. In the contrasting second mode, the domain knowledge holder is a domain expert, supporting analysts to understand data, patterns, results and their implications because analysts lack the knowledge (Ittoo et al., 2016; Janssen et al., 2017; Richards, 2016; Watson, 2014). This promotes cross-functional teams in which key personnel from different functions represent the needs of their respective function and communicate the progress and result to it (Bose, 2009; Dutta and Bose, 2015; Rothberg and Erickson, 2017). A hybrid version of these two modes argues for analysts to receive the domain knowledge on the fly during an initiative. They take part in the data collection, get sense of variations, visit premises, and have focused conversations to gain a comprehensive and holistic view, as well as create conditions for cooperative work on the solution with domain experts (Kenett, 2015; Viaene, 2013). This hybrid counters missing communication on important features of the domain by experts, which take them for granted, requiring scrutiny of analysts.

Regarding interaction, two idiosyncratic modes have been identified with two hybrids. The first mode is the centralization of analysts in a separate unit as center of excellence , which deploys analysts into domains on demand (Debortoli et al., 2014; Grossman and Siegel, 2014; Lavalle et al., 2011). Advantageously, an organization's Analytics expertise is shared in that unit, including governance, tools, methods and specialized expertise creating a more consistent level of effectiveness across domains (Kiron et al., 2012; Lavalle et al., 2011). This is especially useful for predefined questions reoccurring across domains (Debortoli et al., 2014). However, it creates distance between analysts and domains and potentially reduces analysts' understanding about domains and awareness of their needs (Grossman and Siegel, 2014), and is vulnerable to organizational politics (Kiron et al., 2012). In contrast, analysts can be organized domain-specific and decentralized (Carillo, 2017; Grossman and Siegel, 2014; Wedel and Kannan, 2016; Wixom et al., 2013). The popularity of this approach can be observed in the richness of domain-specific job postings (Carillo, 2017; Debortoli et al., 2014). When the need for Analytics is initially recognized, closeness is desired, and this mode creates close collaboration between analysts and domain representatives, leads to tailored solutions to domain requirements, and provides analysts with freedom to explore and experiment (Grossman and Siegel, 2014; Kiron et al., 2012; Lavalle et al., 2011). However, this siloed approach ignores the commonalities of tasks across domains, which would allow exchange with potential benefits, eliminate the need for tailored solutions, and saves resources. It can result in skill gaps, isolated expertise, and a lack of leadership to harness and develop analysts, resulting in domains left behind (Carillo, 2017; Grossman and Siegel, 2014; Wixom et al., 2013). It delays the development of broad expertise across the organization with flexibility to respond quickly to emerging issues without excessive overhead (Wedel and Kannan, 2016).

Two distinct hybrid modes are discussed below, while a multitude of gradations is imaginable. First, analysts can be rotated through several domains by assignment exposing them to several domains and facilitating their interaction with key stakeholder (Harris et al., 2010; Harris and Craig, 2011; Wixom et al., 2013). That way, analysts are more aware of the organizations main activities, challenges and processes and develop more understanding of the organization overall including strategy and value creation potential from Analytics solutions (Harris et al., 2010). Thereby, the fit to strategy is indicated as a distinguishing factor between low and high performers (Cao and Duan, 2017). Rotation further creates exchange between domains and stimulates the adoption of Analytics across domains (Lavalle et al., 2011). The rotation can be vice versa, such as domain experts being deployed to Analytics functions as support as well (Wixom et al., 2013). The second hybrid organizes analysts by deploying some Analysts in domains and keeping some centralized (Debortoli et al., 2014; Grossman and Siegel, 2014; Watson, 2014). This hybrid accounts for problems which can be performed by generalists and for business problems requiring highly specialized Analysts, which should be strongly familiar with the domain (Debortoli et al., 2014; Grossman and Siegel, 2014). For example, problems without predefined solutions or of an experimental nature that might include innovative technologies and concepts.

3.3 Methodology

This research aims to explore characteristics of Analytics initiatives setting domains apart exemplified on the LSCM domain. This aim requires a research design facilitated in empirical data. Since the research about these individual aspects is limited and incidental in existing literature, this research is exploratory. Thus, a Grounded Theory approach has been chosen using semi-structured interviews for data collection (Manuj and Pohlen, 2012; Strauss and Corbin, 1998).

Grounded Theory combined with semi-structured interviews was used previously in LSCM research to map phenomena and develop distinctions. Grounded Theory was employed to map themes and properties of enhanced communication that have explanatory value for differences in business performance in the employee-to-employee relationships between supply chain organizations (2012), benefit categories of supply chain clusters have been identified with detailed reasoning of distinction (Rivera et al., 2016), and definitions of supply chain complexity and supply chain decision-making complexity have been designed, and antecedents, moderators, outcomes and interrelations have been identified (Manuj and Sahin, 2011). Summarized, Grounded Theory generates depth and understanding of research topics in LSCM when little is known about the research subject and is resultingly suitable for this research.

3.3.1 Sample and data collection

Initially, experts on SCA were contacted for interviews, but these experts expressed their concern about their inability to make statements about differences of LSCM as compared to other domains, since their experience is limited to one domain. Consequently, experts with experience in executing Analytics initiatives in different domains were sought by approaching "Data Analytics Companies" (Beer, 2018). Specifically, experts in these organizations were contacted and asked about their experience with different domains and their experience with LSCM. Experts that signaled knowledgeability about LSCM and several other domains were asked for interviews. For this purpose, a list of top solution vendors and integrators for Analytics was extracted from market reports. A list of 110 "Data Analytics Companies" was compiled and participants from managerial and senior positions were chosen for establishing contact. An initial sample of interviewees has been sought based on experience, job title, profile and willingness to participate. Subsequently, theoretical sampling was used in accordance with the Grounded Theory approach (Manuj and Pohlen, 2012; Mello and Flint, 2009; Strauss and Corbin, 1998). Thus, the choice of contacted experts was determined by the emerging theory from analyzing the conducted interviews. With emerging theory, interviewees were recruited with the objective to develop further understanding in certain aspects. Therefore, personal and company profiles were taken into focus, while job title and experience requirements were relaxed. Later interview requests targeted more technology focused organizations as well as experts in Prescriptive Analytics topics. Eventually 13 interviewees have been recruited resulting in twelve interviews including one interview with two interviewees. For reasons of anonymity, position and organizations are presented as lists:

- Positions: Head of Analytics (2), Director Analytics (3), (Senior) Manager Analytics (3), Consultant Analytics (2), Solution Architect Analytics (3)
- Organization: Solution Vendors (5), Solution and Service Vendors (2), Consultancy (1), Solution Vendor and Consultancy (2), Integrator (1), Service Vendor and Consultancy (1)

Figure 9 summarizes the years of experience distributed over interviewees as well as the interview duration. Interviews were conducted via telephone and VOIP conference systems. During the interviews, handwritten notes were taken for the purpose of recording and guiding the interview. The interviews were audio-recorded if permission from the interviewees was granted. Audio-records were transcribed and deleted afterwards.

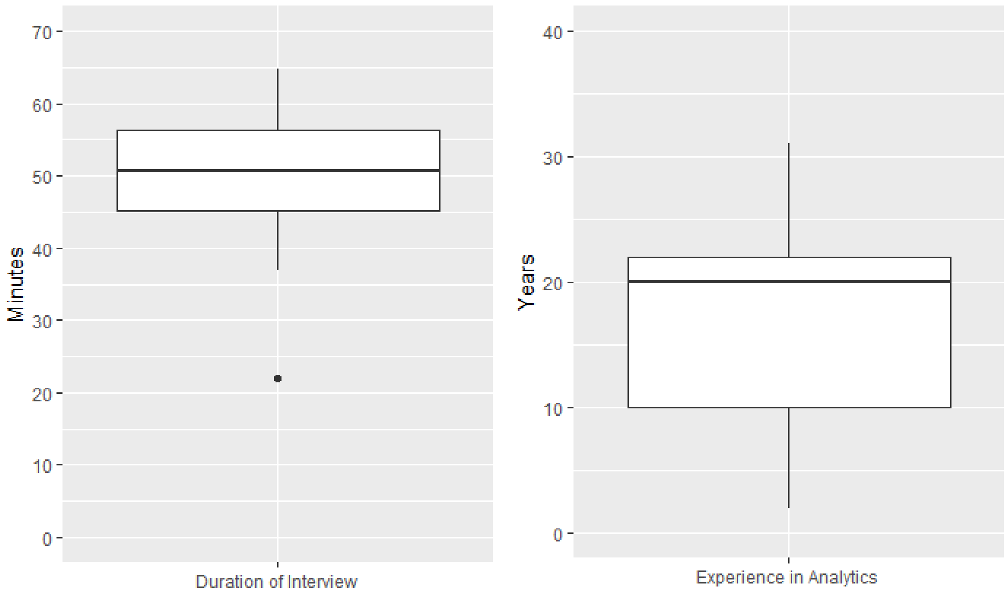

Figure 9: (left) Duration of Interviews with Experts, (right) Experts Experience in Analytics

Following the recommendations for Grounded Theory (Strauss and Corbin, 1998), interviews were started with grand tour open-end questions (McCracken, 1988). First, interviewees were asked about their understanding of the terms “Analytics” and “Data Science”. Second, they were openly asked about the differences of Analytics initiatives executed in LSCM compared to other domains. Subsequently, the open questions were extended by focused questions. To provide a systematic examination of the interviewees’ experience and knowledge, interviews were structured on cause categories from the Ishikawa diagram – a tool for identifying causes. Eight cause categories were used in this approach (2016). These originally generic cause categories were adjusted to Analytics by referencing the cause categories to more specific topics from Analytics. The approach was used to provide a systematic and broad focus of differences to discuss with the interviewees. The categories are as follows: People (users and domain experts), Methods (analytical and initiative management), Machines (hardware and software), Material (data), Measurement (metrics of success, objectives), Environment (partners and external data), Management (organizational management), and Maintenance (solution maintenance).

Interviewees reported the differences of domains in executing Analytics initiatives to be nuances. However, these nuances corresponded to the characteristics aspired to identify. Thus, the characteristics, or rather phenomena (1998), and how they influence Analytics initiatives were mapped as presented in section 3.4. Interviewees elucidated the nuances, they perceive, based on Analytics initiatives they have contributed to. The systematically semi-structured interviews lead to three forms of characteristics: (1) interviewees presented distinguishing characteristics of LSCM from other domains, (2) interviewees explained characteristics with differentiation potential through examples that distinguish other domains and commented that LSCM does not differ from the majority of domains, (3) interviewees explained distinguishing characteristics that were previously different in domains but not currently. The latter was primarily influenced by the current hype-level of Analytics causing changes in the characteristics across domains.

3.3.2 Data Coding and Analysis

Data was analyzed in accordance with the guidelines of Grounded Theory as described by Strauss and Corbin (1998). In the first step of the analysis of interview transcripts, open coding was performed following each interview with the intention to incorporate new aspects into the subsequent interview. In open coding, the interviews were conceptualized on a sentence-by-sentence basis by labeling them with short explaining phrases or terms. Similar statements were given the same label. The labels, and concepts they represent, were used to identify "categories" in subsequent steps, which reflect phenomena such as events, conditions or actions/interactions. After twelve interviews, theoretical saturation was attained such that incremental interviews were not expected to yield additional information. The analysis was performed using the ATLAS.ti software and resulted in 90 labels. After all Interviews were conducted, following Strauss and Corbin (1998), the labels were reevaluated to discover the categories. Thus, the concepts were grouped under higher order categories with an improved ability to explain or predict phenomena. For this purpose, a category by category comparison was conducted. Resulting higher order categories were subsequently given names with explanatory value and these categories were developed into phenomena by using the interview chunks to derive explanations describing the phenomena and delineating them from other phenomena. These steps eventually concluded in 34 categories.

In the second phase of axial coding, links between categories were systematically developed by using the paradigm scheme and its components (Strauss and Corbin, 1998). The paradigm scheme components recommended by the Grounded Theory guidelines are conditions, actions/interactions and consequences as illustrated in Figure 10. Conditions are divided into causal conditions, which influence other phenomena, contextual conditions, which have their source in causal conditions and create circumstances or problems to which persons respond through actions, and intervening conditions, which mitigate or alter the impact of causal conditions and must be responded to by actions. Actions represent strategies devised to manage or respond to a phenomenon such as causal conditions. Consequences are outcomes or results of actions.

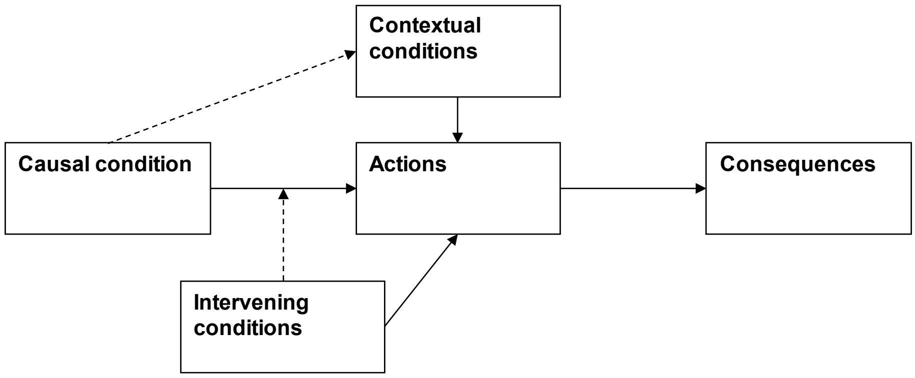

Figure 10: The paradigm scheme of components

In the final phase of selective coding, categories and components were integrated and refined (Strauss and Corbin, 1998). Thereby, more detailed and comprehensive explanations on phenomena were derived by revising them to indicate connections to other phenomena according to the data. Appropriate to this purpose, the components from axial coding have been split such that connections could be revised to represent the links in accordance with the data to form a well-developed map of characteristics of Analytics initiatives potentially setting domains apart.

3.3.3 Trustworthiness

Following previous studies using Grounded Theory in LSCM research (Gligor and Autry, 2012; Manuj and Sahin, 2011) and studies reviewing Grounded Theory approaches (Denk et al., 2012; Manuj and Pohlen, 2012), multiple criteria for trustworthiness were collected. These criteria are credited to the Straussian School of Grounded Theory, which was followed closely in the research. The following criteria were addressed: (1) Credibility was addressed by providing a summary of the phenomena with descriptions and links to the participants for feedback and reflection; (2) Transferability was ensured by applying theoretical sampling; (3) Dependability was addressed by following the guidelines of Strauss and Corbin for Grounded Theory (Strauss and Corbin, 1998) and McCracken for interview design (McCracken, 1988); (4) Confirmability was aspired by a technique using an altered form of bracketing (Kvale, 1983) as described by Manuj (2011), which requires the authors to write down the essential points known about the research subject. The pre-existing knowledge was afterwards compared to the results. Phenomena that overlapped in pre-existing knowledge description and results were reviewed for existence in the transcripts; (5) Integrity was established by maintaining anonymity of the interviewees; (6) fit was ensured by the methods for credibility and dependability; (7) Understanding was also addressed by the summary provided to interviewees and the inquiry to feedback and reflect them; (8) Control was given to interviewees who had some control to direct the interview to topics they perceived as important; (9) Generality was aspired with the length and open questions of the interviews and the subsequent systematic structure intended to cover as many areas as possible.

3.4 Results and discussion

This section explores the results by presenting the characteristics of Analytics initiatives differentiating domains and specifics of LSCM.

3.4.1 The map of characteristics of Analytics initiatives differentiating domains

The characteristics derived from the data analysis have been map according to the paradigm scheme of Strauss and Corbin (1998). Due to substantial differences of characteristics allocated to components, the components have been further segmented. This resulted in eleven sub-components with 32 characteristics of Analytics initiatives differentiating domains. A twelfth component has been created describing the concept of Analytics, which is independent from the domain. The components and their characteristics, which are explained in the upcoming section, are illustrated in Figure 11.

3.4.1.1 The concept of Analytics

Two domain independent characteristics were identified, which describe the interviewees' conceptualization of Analytics and distinct roles and attributes of Analysts.

The term degrees of Analytics hints at the degrees of business intelligence of Davenport and Harris (2007) and addresses different levels of complexity of analytical methods. However, they represent contemporary complexity levels, which are subject to change over time. Analytics has been recognized as most complex degree of analytical methods to the overall concept of Business Intelligence twelve years prior (Davenport and Harris, 2007). However, the interviewees of this study recognized Analytics as overall term, with Business Intelligence as least complex degree, Analytics, with a second function for the term, as label for the moderate degree, and data science as most complex degree of analytical methods. In the introduction, the terms were expressed as being hard to distinguish and interviewees explained this as somewhat artificially created. The methods and technologies constantly evolve, but distinct labels advertised as innovations help to draw attention to the topic. This attention helps to either market evolved analytical concepts to more mature organizations for new use cases or present interesting opportunities to organizations less experienced in Analytics. Resultingly, this leads to confusion but helps to increase the popularity of analytical methods. In regard to this, a label similar to "cognitive intelligence", an invented term to describe the business version of artificial intelligence (Maissin et al., 2016), might be a plausible candidate for the next label. In short, Business Intelligence is currently understood to comprise methods of manually and experience- or intuition-driven analysis of structured data, mostly from data warehouses, vulnerable to human bias and with less advanced methods. Analytics is understood as comprising more advanced methods on structured data resulting in model- and algorithm-driven insight relying on human intuition and experience to a lesser degree. Data Science was understood by interviewees to refer to the most complex and advanced analytical methods (machine learning, advanced statistics) supposedly minimizing human bias and applied to unstructured data as well, often with a more experimentation and proof-of-concept focus as opposed to driving business decision-making.

Four Analytics roles were extracted, which are justified to exist in parallel in an organization. First, business users use embedded analytical functions from software accessible to them. Second, controllers aggregate and group data and numbers and must assure correctness of data for the purpose of reporting higher management as well as legal authorities. Third, business analysts are business function-specific analysts familiar to some advanced methods for structured data in terms of purpose and application with the intend to produce consumable insights for management or other non-analysts. Fourth, data scientists are application developers with a full range of knowledge about methods and tools at hand, from simple methods in graphical user interfaces to advanced methods applied "at the command line", who have deep technical and analytical knowledge and

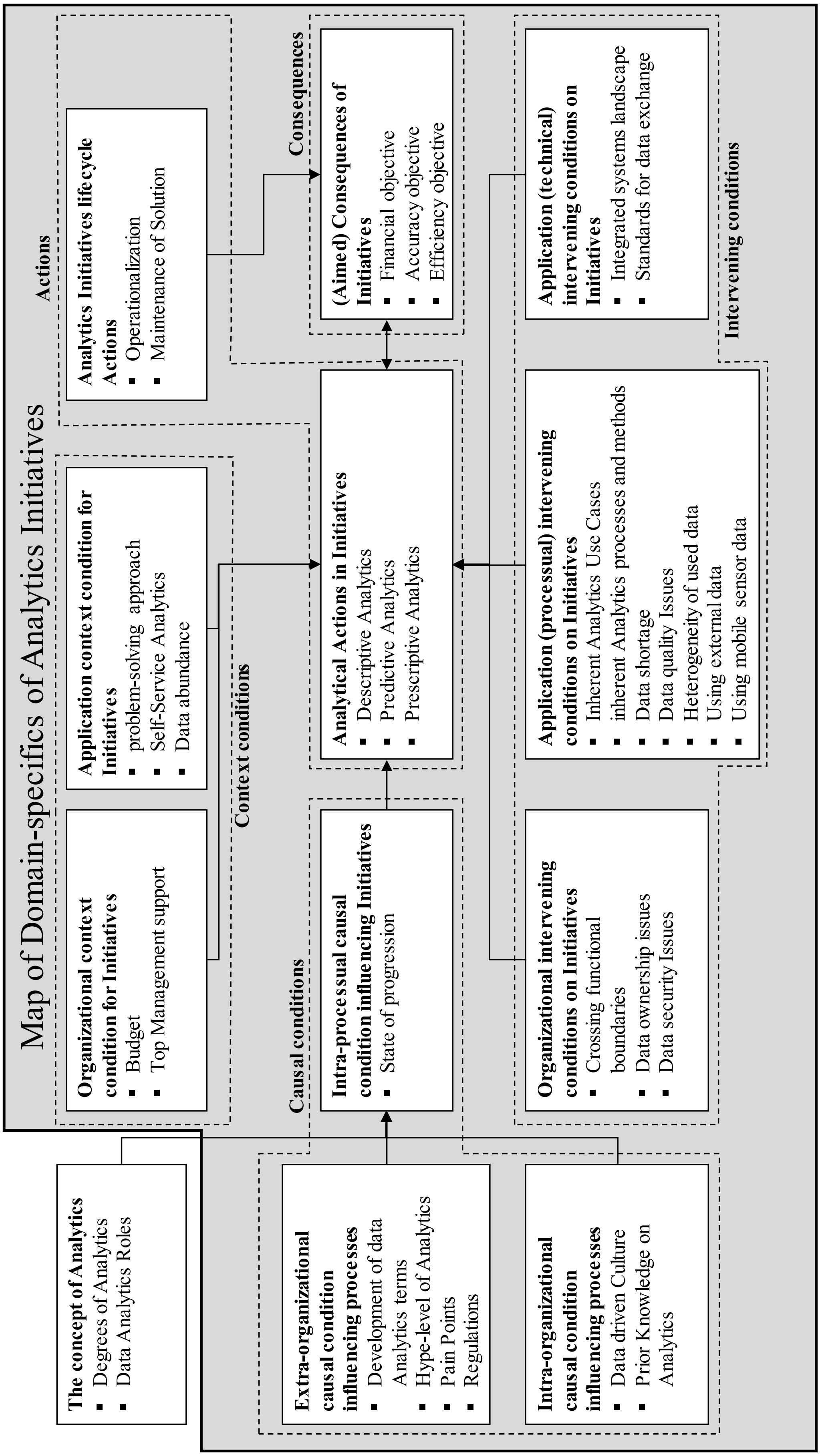

Figure 11: Map of domain-specific aspects of Analytics initiatives

skills and try to stay up to date on methods. Their jack-of-all-trades-image was rejected in the interviews and they were rather criticized for their tendency to produce non-consumable results for non-analysts and to develop applications, which are not scalable, reinvent existing concepts and do not address business needs.

3.4.1.2 Causal conditions

Causal conditions represent sets of characteristics influencing other characteristics and conditions that explain why persons, or organizations, respond as they do (Strauss and Corbin, 1998). Due to the interviews, three sets have been identified: extra-organizational causal conditions, intra-organizational causal conditions and conditions influencing Analytics processes in an organization and subsequently the Analytics initiatives.

The first characteristic of **extra-organizational causal conditions** is the mentioned patterns of development of data Analytics terms leading to new taxonomy about “every 5-7 years or so”. The new and unheard-of concepts usually highlight aspects that were already used to a lesser degree in previous iterations. These changes mobilize new groups to use Analytics or existing user groups to identify new use cases domains differently. Second, as infamously represented by the Gartner hype-cycle, technologies and concepts undergo cycles of temporary publicity, leading to changing Hype-levels of Analytics. This results in an eruption of projects to create benefits from data in a sort of “gold rush atmosphere” with exaggerated expectations on profitability and ease of applying Analytics. At the moment of this study, organizations are eager to create Analytics subsidiaries (e.g., Data Labs, Data Factories) with high top management attention, fast to perish if they fail. This kind of adoption based on momentum of other adopters and success stories is also termed bandwagon behavior, which can lead to a mindless adoption as opposed to mindful and thus wary and appropriate to the organization (Fiol and O’Connor, 2003; Swanson and Ramiller, 2004), with domains displaying this behavior in different degrees. Third, interviewees described the rather abstract phenomenon of external pain points that create different stimulus to interest and need for Analytics in different domain. This characteristic was retained as vivo code (Strauss and Corbin, 1998) to express the recurring inability of interviewees to explain it more tangible. This pain point could be something like competitive pressure, reducing environmental impact, regulations or customers demanding Analytics solutions. Forth, a specifically mentioned external stimulus to use Analytics are regulations. The regulatory demand to report various aspects of organizational operations and actions is a strong motivation to deploy

Analytics, especially if future prognoses are demanded such as for the banking domain to avoid market crashes and monetary devaluation.

For **intra-organizational causal conditions**, one characteristic with different impact in different domains is the data-driven culture, which supposedly has a plethora of effects on the application of Analytics in organizations, as discussed by scholars (Holsapple et al., 2014; Kiron et al., 2012; McAfee and Brynjolfsson, 2012). This culture positively influences the cooperation of users and experts within Analytics initiatives, and acceptance and use of the Analytics solution but requires sufficient change management. Otherwise users show unwillingness and devalue solutions ("this is a one-time effect", "data have been flawed and antiquated"). Another characteristic of this causal condition is the prior knowledge on Analytics. This prior knowledge paves the way for the application of Analytics, collaborative initiatives and the use cases that can be addressed. However, interviewees highlighted the background knowledge being less important than the willingness and interest to achieve a successful improvement of processes using Analytics. But this motivation is often dependent on knowledge.

Finally, the causal conditions above influence the **intra-processual causal condition**, represented by the characteristic of state of progression of Analytics. This characteristic refers to maturity, advancement of use cases and adoption rate, that differs across domains.

3.4.1.3 Context conditions

Context conditions describe conditions originating in causal conditions and creating circumstances and issues for Analytics initiatives to which people respond to through actions and interactions (Strauss and Corbin, 1998). In contrast, intervening conditions moderate the effect of causal conditions. The identified context conditions have been grouped into conditions concerning organizational processes and conditions concerning the application of Analytics.

Regarding **organizational context conditions**, the first identified characteristic is budget to execute Analytics initiatives, which might be additionally allocated, reallocated from IT or not allocated at all. It can be allocated goal oriented to create innovations or "halfhearted" by hiring "some Data Scientists" without any ideas for use cases due to hype. In contrast different behavior of domains in the past, organizations across domains are currently allocating budgets into Analytics in magnitudes surprising and unseen by the interviewees, while organizations without financial means wait for technology providers to develop applicable solutions. Second, long-term value from Analytics requires strategic Top Management support, as discussed by scholars (Davenport and Harris, 2007). Interviewees explained strategic vision easily lacking in either IT and business units, with the former prioritizing technical specifications and standardization over functionality and displaying protectionism, and the latter being stuck in daily business or concerned about increased workload. Top management support is required for a goal-oriented course of actions with Analytics, encourage change and create visibility of the value of Analytics – a value that is recognized differently across domains. An interviewee described: "if nobody recognizes the value of an initiative, it will not have success".

Concerning **application context conditions**, it must be recognized that Analytics has low sole standing self-purpose and requires a problem-solving approach to address business problems or cases – “something with a user story behind” – at the core of initiatives, as emphasized by scholars (Herden and Bunzel, 2018). The problem needs to be clearly defined and its solution promise valuable returns, whether for data aggregation of reports or for strategic enterprise-wide analytics initiatives. This business problem was expressed to be more relevant than superior algorithms or models, with timely available solutions “put on the road" being more valuable than non-deployable and delayed superior algorithms. This problem-solving approach proliferates with increasing experience with Analytics but organizations across domains are still performing Analytics initiatives without a problem. These are unlikely to address business needs and result in abandoned pilots, undeployed solutions, or missing users for deployed solutions. A second characteristic and a strategy to ensure to address business problem is to give business users means to apply Analytics by themselves – so called self-service Analytics. However, this requires users’ abilities to apply quantitative methods, while access to data and tools must be provided with only some domains putting it to the test. Third, due to the promised value from data and the technological ease of data collection, organizations across domains experience a data abundance leveling the varying data access in the past. This does not imply access to all the data required for their initiatives. Organizations collect and store data without a specific purpose to harvest the value at a later point in time, while the number of data sources increases constantly, and collection is becoming cheaper. Consequently, they try to harvest value from data forcefully while contradicting the problem-solving approach with sporadic success.

3.4.1.4 Intervening conditions

Intervening conditions mitigate or alter the impact of causal conditions on Analytics initiatives and are responded by actions (Strauss and Corbin, 1998). They contrast context conditions, which are triggered by causal conditions. The identified intervening conditions were grouped into organizational conditions, conditions concerning the process of executing Analytics initiatives and conditions concerning the required technologies.

The first **organizational intervening condition** was mostly recognized as specific to the LSCM domain, which is the crossing of functional boundaries. The characteristic describes data being collected, stored and owned by partners and Analytics solutions required to be deployed across boundaries to these partners as well. However, boundaries can already occur in the same organization between business functions, which are rarely crossed in some domains. A closely linked second characteristic is data ownership issues. Thereby, as opposed to the previous characteristic data owners with no business relationship are considered, which possess relevant data. Data collected by a third party or using a technology of a third party is often owned by that third party resulting in additional agreements. These are increasingly used in some domains as source of revenue – "most data owners have recognized the revenue potential by now" – and increase the cost of Analytics initiatives. Unwillingness of this third party can further prevent access to necessary data for an initiative. This issue is interrupting organizations across all domains, but interviewees suggested that organizations could accept Analytics solutions from data owners instead, while saving resources by buying (decision-ready) insights. Third, the characteristic of data security issues is usually a major concern in domains with highly sensitive data required to protect privacy of individuals. This induces steps to limit access to data or to anonymize them complicating their use in analytical methods and demands additional infrastructure in hardware and software to increase protection against unauthorized access.

The category of **application (processual) intervening conditions** is the largest. The first characteristic, interviewees unanimously agreed upon to be the main and most tangible distinction coming differentiator of domains, is the inherent Analytics use cases. This is self-evident, since the business tasks, processes, objectives, roles, people filling the roles, their knowledge and their vocabulary are different. Thus, metrics, data, and requirements of Analytics Solutions are different resulting in various use cases inherent to every domain. However, some use cases recur in numerous domains. Second, interviewees agreed unanimously upon the lack of domain inherent Analytics processes and methods. Analytics is characterized by the transferability to any domain. This includes the process of executing initiatives, the process management techniques and, in particular, the "very transferable" analytical methods. However, choice and adjustments of a methods are dependent on the specific use case resulting in some methods being used more often in certain domains. Third, while there is some abundance of data as explained above, for certain problems and use cases a shortage of data can occur in some domains, since not everything interesting is currently collected or collectable. The required data collection technology may not exist or is not available for a reasonable resource commitment. Thus, the development of a technology or its reduced price can spontaneously enable a range of organizations to execute certain initiatives such was with internet-of-things (IoT) sensor data as discussed below. Fourth and closely linked to data shortage are data quality issues, which have been indicated as cross domain issues (Hazen et al., 2017) but to varying degrees in different domains. They result from false entries, missing entries, conflicting entries and unstandardized data entries and prevent integrated analysis and more complex Analytics initiatives, which can even occur in the same organization. Hence, resources are redirected from Analytics initiatives to initiatives to integrate data. Fifth, as discussed above, for complex analytical approaches, usually several data sources must be combined crossing boundaries of organizations, business units or process steps leading to issues with heterogeneity of data as a characteristic. Even comparable processes may entail different machines or different people in charge of processes and, thus, create differences in data (e.g., data collection frequency, data availability, data structure, or data granularity). As a result, integration binds resources otherwise used for insight generation in some domains. Sixth, a contemporary stimulus for adopting Analytics is the use of external data, due to wide applicability and increased availability. One interviewee explained that "as of now, using external data is common sense" and most domains use them for improved results (e.g., for LSCM, data on infrastructure, weather, traffic, natural disasters, political conditions, and regional customer characteristics and preferences). Finally, the use of mobile sensor data has increased due to advances in their technology and especially integrability and remote data access ability. In particular, the characteristic is becoming quite relevant in some domains, and resultingly distinguishing it from other domains, due to IoT sensor devices, transmitting data via GSM or other mobile signals. These sensors create access to new kinds of mobile data (e.g., ambience, vibration, brightness, sound level, movement, image-based condition, position), while data becomes available in a higher granularity and frequency.

Concerning **application (technical) intervening conditions**, some domains experience issues in these conditions that increase the impact of issues discussed in previous categories. The first technological characteristic altering organizations ability to apply Analytics is an integrated systems landscape, which enhances Analytics if present and obstructs otherwise. The replacement of outdated systems, which lack the performance of modern systems, can be too great of a risk for organizations dependent on these systems' functionalities and worrying about losing them. System landscapes grow naturally and so are their data structures resulting in established organizations losing overview of their systems in terms of functionality and operating method as well as in inappropriate or missing updates to the systems. Once deliberately employed tailored and task-specific systems lack scalability and integrability in focus of today's systems landscapes and, nowadays, the effort of orchestrating these systems is challenging and resource consuming. Start-ups and younger organizations are usually spared from these challenges but most organizations in established domains cope with them and must redesign their systems landscape. A second prominent characteristic that creates challenges for organizations in execution of Analytics initiatives is standards for data exchange. Internal data exchange standards are averted from legacy systems in the systems landscape or overturned by merger and acquisition. Externally, some domains developed standards for certain data exchange processes such as the EDI (Electronic Data Interchange) standard, but these are usually barely sufficient for Analytics requirements. The currently used interface landscape created to enable data exchange is argued by interviewees to be sufficient for current needs and the development of a standard would lack a necessary authority such that scholars' demand for a common shared understanding on the definition of standards and interfaces (Kache and Seuring, 2017) might not be met any time soon.

3.4.1.5 Actions

Actions represent strategies devised to manage, handle, carry out or respond to conditions (Strauss and Corbin, 1998). Thus, the analytical actions identified in this study are initiated or altered by the various identified causal, context and intervening conditions. Distinguished are Analytical actions in initiatives that represent the use cases of analytical methods and actions related to the lifecycle of Analytics initiatives.

In accordance with a widely recognized perspective, the **analytical actions** in initiatives are distinguished in Descriptive, Predictive and Prescriptive (Holsapple et al., 2014; Souza, 2014; Wang et al., 2016), which were explained by interviewees to represent complexity levels but only to a limited extent. All approaches employ (relatively) simple and complex methods and initiatives usually demand the combinations of different approaches. Regarding the first approach of Descriptive Analytics, the methods are predominantly less analytically complex with rule-based data aggregation analysis. However, they can become technically complex when several heterogeneous data sources are supposed to become integrated. Currently, interviewees experience high demand for such initiatives from organizations in some domains attempting to create "a single version of truth" of their complex operations in likewise complex organizational structures, which are not manageable by intuition anymore and require data-driven decisions and control. The created insight embodied in reports, key performance indicators and dashboards is usually post-operational and provides transparency and visibility of the status of the daily business, mismatches of results to expectations, weak spots, benchmarks for different decisions, and needs for actions – not necessarily which actions. It was credited as "good entry level Analytics approach" by interviewees but creates meaningful insight, nonetheless. The second characteristic, or rather approach, is predictive Analytics, which is currently broadly requested across domains, while some domains took time to catch on. Famous due to demand forecasting, predictive Analytics provides use cases for most domains, while it is deployed in higher or lower analytical complexity. Third, prescriptive Analytics mostly consists of the application of optimization methods. While more complex optimization use cases are concentrated to few domains, the methods are generally used in most domains. Further, the applied methods are used sometimes applied to simpler repetitive problems and as such provided as features to software tools without further individualization leaving potential for improvement.

Regarding the **lifecycle actions**, the identified characteristics concern the benefits of analytics initiatives in the short and long term and issues in these characteristics can eradicate any productive activities in the previous steps of the initiative. First, a currently major issue in many domains is the operationalization, the so-called deployment, of Analytics solutions. There is a shift towards providing more Analytics solutions directly into operational processes to improve decision-making at the operational level instead of the managerial level only. The insights are used faster and the users at that level work naturally with insights since it is based on their tasks and decisions. Further, they are incentivized to collect and insert data more carefully because they get better insights or better processes in return. However, this phase is prone to be underestimated in planning of the initiative, and challenges, overlooked user requirements and the heavy resource consumption can result in abandoned pilots. Second and similar, the subsequent maintenance of developed Analytics solutions, such as algorithms and models, is supposed to ensure correctness, adaption to the process, persistence of accuracy or adjustment to new patterns in newer data. As scholars indicated, this requires a continuous monitoring and evaluation of even proven useful analytics solution (Leventhal, 2015). However, while users are familiar with updates for software, maintenance of Analytics solutions is in some domains alien to them that lack maturity in Analytics.

3.4.1.6 (Aimed) Consequences

Finally, consequences are the outcome of actions and as such the outcome of the investigated Analytics initiatives. Corresponding to the research method, the consequences below refer to intentions and aims.

The first and foremost aimed **consequence** is the characteristic of aspiring the financial objective, whereby short-term costs savings and revenue increase must be distinguished. Analytics tends to provide direct benefits (improving processes, increasing revenue), which induce indirect monetary payoffs as cost savings. An initiative must be cost effective in this indirect way, since it displays an investment that is supposed to create an output higher valued than its input like any other investment. The financial objective, which is pursued in some domains, stands outside of this cost-effectiveness and refers to direct cost savings and increase revenue. However, interviewees usually addressed non-monetary objectives. Second, one non-monetary objective is the accuracy objective referring to the need for high accuracy of Analytics solutions due to criticality of business processes. Criticality can result from domain-specifics such as possible harm (e.g., pharma, aeronautics), adherence to laws (e.g., taxes), or costs of inaccurate decisions (e.g., consumption of low margins in retail). Consequentially, users must communicate reasonable requirements on the accuracy, since it influences the dimensions of Analytics initiatives. Third, another non-monetary objective is the efficiency objective regarding processes by identifying and eradicating inefficiencies. This may concern the identification of sources of lost time, insufficient quality, or waste and creation of monitoring solutions that support control of these inefficiencies.

3.4.2 Specifics of the LSCM domain

LSCM shows several differences in the mapped characteristics in all components except context conditions, which are discussed below. This implies benefits from domain-specific research with extensive domain knowledge on the issues. However, the majority of characteristics, not discussed below, represent characteristics of Analytics initiatives that allow cross-domain research for improved approaches or to create measures to overcome barriers.

3.4.2.1 Specifics in causal conditions

Interviewees attested a certain scarcity of pain points in LSCM leading to low perceived external pressured to use Analytics as compared to other domains. Organizations in LSCM are usually driven by the internal needs to handle and control the daily business and operations motivating the use of Analytics if this control is perceived as unsatisfactory. Customers may create an indirect stimulus by demanding more efficient services, but only few customer requirements specifically demand Analytics and, especially, few were reported to demand Analytics solutions beyond market available solutions that necessitate Analytics maturity.

Considering regulations in particular, LSCM was also reported to have fewer and less complex regulations, but still has to report things like journey times of drivers or compliance to customs, taxation or customer requirements. Environmental regulations were speculated to potentially increase the use of Analytics in LSCM but the current influence of regulations on the state-of-adoption of Analytics in LSCM is low compared to other domains.

Interviewees reported to perceive LSCM as more directed towards an intuition-driven culture as opposed to a data-driven culture, which was, however, described in aspects to comparable to a lock-in effect to solutions. LSCM is an early user of analytical methods in certain processes and these solutions are trusted with hesitance to use other, allegedly more advanced, methods. Thus, the culture is less data-driven relative to newer Analytics approaches and the issue is one of change management.

Respondents experienced the people in LSCM, relative to other domains, as less imaginative in the use of data, having a lower degree of experience in working with data in comparison, and a higher need for explanation – having less prior knowledge. Considering the range of activities in LSCM, the domain has an apparent demand for workforce without the requirement for a formal education in statistics or higher mathematics, while members of this workforce, on the condition of showing a satisfactory performance and due to their "floor experience" (Rivera et al., 2016), can rise to management positions. However, people in LSCM are perceived as interested (and proud) in improving their processes and finding solutions for their problems leading to the flexibility to test several solutions with a hands-on mentality. Thus, interviewees observed two outcomes of this: if a solution has been found to which people have become accustomed to, they are harder to convince to change course. otherwise, they are open to new solution attempts including Analytics, but the problem to be solved is resultingly intense.

Regarding the state of progression, LSCM is perceived to occupy a stable midfield position. In contrast, other domains are perceived as more volatile – sometimes leading, sometimes trailing. Respondents report to execute Analytics initiatives now in LSCM, they have executed decades ago in domains like banking and telecommunications. This current state was reflected to be caused by missing data and technology which is now available and can give LSCM a momentous potential to catch up with some organizations already exploiting the potential. However, this potential requires interest or pain points to become exploited.

3.4.2.2 Specifics in intervening conditions

In accordance with the foundational idea of LSCM of creating a conjunction between different actors to transform raw material and distribute resulting products to consumers, LSCM organizations have a substantial number of links to customers, suppliers, service providers, other business units and other partners. Thus, LSCM constantly crosses internal and external functional boundaries on physical processes and would greatly benefit from doing so an Analytics initiatives in a more natural way as compared to other domains (e.g., new business models between wearable technology providers and insurance organizations). However, issues arise from data collection or distribution of Analytics Solutions crossing functional boundaries. First, due to global distribution of partners and organizational distance, a different need for collecting or exchanging data is perceived or resulting transparency is feared as loss of power and influence, even in the same organization. Second, cultures differ in attitudes towards collecting and exchanging data. Third, technological infrastructure and systems differ complicating data exchange. The organizational distance increases further with requests for data exchange cascading to organizations with indirect business relationships (partners of partners). In reverse, insights from Analytics solutions might be necessary for partners leading to deployment across functional boundaries. This increases scalability and adaptability requirements of the solution, which increase development time and reduce the interest of solution sponsors unwilling to pay for benefits outside their area of responsibility. Lastly, due to limited contract duration, exchange of partners and changing customer preferences, the Supply Chain network is in constant motion such that cross functional Analytics may have a short durability.

In contrast, interviewees did not observe demanding requirements in terms of data security in LSCM, since for most use cases organizational assets and processes are analyzed as opposed to individuals. Of course, customer preferences analyzed for demand prediction entail privacy concerns, but such concerns are far more regular in other domains.

This study further specifically inquired data quality issues, since scholars indicated the considerable impact of human data collection errors (Wang et al., 2014). This has been confirmed by some interviewees but was evaluated as minor component of the data quality issue and its effect comparable to any domains. Further, data collection is increasingly becoming automated such that this impact is erased in the long run.

In conformance to the crossing of organizational boundaries, the heterogeneity of data is natural to LSCM as well, coming from diverse business functions and partners. In LSCM, this binds resources for creating interfaces such that interfaces are created to partners with reasonable importance and longer expected partnership lifetime. Put differently, the effort is not invested for every partner hindering potentially interesting initiatives.

Finally, LSCM is a favorable candidate to use mobile sensor data and has an affinity for using it from mobile assets (e.g., ships, trucks, airplanes, trains, elevators, manufacturing machines) and shipments (e.g., containers, packages, work-in-process). This innovative technology represents a paradigm shift in LSCM from collecting event-based data at stationary points to a constant monitoring, which provides value by reduced reaction time on incidents. The integration of IoT data is complex and creates large effort in wide scale implementations but is already technologically manageable. Hence, organizations are still pioneering with the technology such as a few LSCM organizations that start to monitor and control their, ideally, permanently moving goods and assets such as in real-time status visualization. However, organizations struggle with initiatives to extract higher forms of insights and few attempt more complex use cases like ETA-Prognosis, (dynamic) route optimization, and incident-based product allocation or product reordering. Other domains certainly have use cases for this technology, which are, however, less apparent.

3.4.2.3 Specifics in actions

Since it is strongly related to the use cases, LSCM shows clear domain-specifics in the differentiating characteristics. Regarding descriptive Analytics, LSCM shows an above-average demand for aggregated data from widely dispersed data sources, including IoT, in real-time such that operational processes can be fine-tuned and adjusted based on the most appropriate decision to even complex issues, if necessary. LSCM operations have been streamlined and usually include few buffers, which demand precise real-time data to react to short term incidents and changes. Resultingly, current Descriptive Analytics problems in LSCM display high technical complexity, while some remain to have aspired solutions but not achieved them.

Regarding Predictive Analytics, LSCM was indicated to trail behind other domains. While scholars (Waller and Fawcett, 2013) have emphasized the potential of use cases such as forecasting of demand, delivery time or customer behavior, interviewees barely experienced these use cases from LSCM. They observed that these use cases are either on the long-term agenda due to missing data or are inputs for Prescriptive Analytics, whereby the development focus is on the Prescriptive part with acceptance for standard solutions for the Predictive part (e.g., predictive maintenance of assets focused on resource efficient repairs scheduled into operations).

For the Prescriptive Analytics part, interviewees perceive an extraordinarily position of LSCM, since there is a natural association between Prescriptive Analytics methods and LSCM optimization problems, which “are so beautifully tangible”. LSCM has complex planning problems of goods and assets to be allocated or moved through the network against its capacities. However, it was also observed that these problems are solved with standard features of some software, which are not further individualized and leave high potentials for improvement. Interviewees described further aspects of complexity. First, LSCM is eager to exploit Prescriptive Analytics solutions for identification of alternatives and impact of what-if scenarios to develop superior reactions in beforehand, including dynamic adjustments of operations, which were already initiated according to the previously optimal solutions, to situational changes with as little effort as possible. Second, LSCM problems tend to be more complex due to characteristics of problems and numerous restrictions, which additionally change along the supply chain. As scholars noted, the idea of holistically optimized efficient networks leads to optimization problems in LSCM getting very large very fast (Blackburn et al., 2015).

Considering the maintenance of Analytics solutions, some domains experience an extensive need for adjustments and verification due to fast degrading model quality or high impact of small degradation. In contrast, domains like LSCM with high efforts for data collection or deployment of updates tend to maintain solutions less frequently. LSCM was perceived by interviewees to have low need for maintenance, favoring the complete replacement of solutions in the long run.

3.4.2.4 Specifics in consequences

Interviewees indicated less demands regarding accuracy from LSCM. They have observed that certain decision-making processes are often well-supported by tendencies. LSCM was observed to focus particularly on the efficiency objective, what overlaps with the extensive development of tools to increase efficiency (e.g., lean, continuous improvement). Respondents emphasized that results from Analytics solution in LSCM usually lead to decisions on physical operations, of which the resource consumptions is supposed to be minimized.

3.5 Conclusion and directions for further Research

Research on Analytics is often limited to one domain, while it is a transferable tool that can benefit from cross-domain development efforts. To identify promising aspects of Analytics to cooperate research on, characteristics to set domain-specific and independent issues apart are necessary but have not yet been provided by research. This study has investigated these characteristics and identified specifications of the LSCM domain based on Grounded Theory. The derived map displays a theoretical model of characteristics potentially differentiating domains principally, contemporary or have in the past. This map displays antecedents influencing procedure and success of Analytics initiatives and can guide Analysts and managers for prioritization of issues.

3.5.1 Theoretical Implications

Relating to the purpose of this research, the main contribution are the characteristics of Analytics initiatives, their connection – their mapping – and their use to differentiate LSCM from other domains executing Analytics initiatives. The map provided by this research distinguishes the characteristics in different conditions, actions and consequences. The mapping of characteristics provides explanatory value on differences of Analytics initiatives' success and performance far beyond the Analytics method and approaches itself.

This research adds to the limited literature on the effect of the domain on Analytics initiatives and provides an extensive overview on effects contributing to procedure, success, and users attitude towards it, and therefore characterize an initiative. These characteristics can be used for further quantitative research on issues of Analytics.

Concerning the LSCM literature, the theoretical model emerging from this research provides antecedents of Supply Chain Analytics. It emphasizes the potential of the LSCM domain to advance in Analytics due to recent technological progress enabling further use cases which should be supported and monitored by research efforts. In particular, research is needed on the exploitation of IoT data and the individualization of prescriptive Analytics solutions. For both, research is required to simplify the adoption of the results for organizations. Further research is required to facilitate change management towards more advanced analytical methods and presentation of benefits from Analytics.

This research also highlights organizations coping with issues far off from the consideration of research. Easily said recommendations to advance in Analytics, such as standardization and investments in IT, pose major challenges for organizations with implications and issues unconsidered by research. Thus, by highlighting the complexity of Analytics with this research embodied in the variety of mapped characteristics, research shall be cautioned not to bypass the practitioners needs.

Concluding, this study provides a novel approach to understand the execution and success of Analytics initiatives and provides a multitude of new areas demanding deeper investigation and further research. Thus, this research makes a valuable contribution to the LSCM and Analytics literature.

3.5.2 Managerial Implications

This research accumulates a vast number of recommended actions and behavior for managers executing Analytics initiatives. Before starting an initiative, managers should identify technical and organizational challenges and prerequisites on the map of characteristics to avoid later issues. Managers should further avoid hype-triggered initiatives but rather create well-thought initiatives comprised of a valuable problem to be solved, a potential user meaningfully contributing to the solution's development, a sense for the user story of the solution providing implications for the deployment, and maintenance needs for long-term performance persistence. To gain the users help, trust and willingness to use the solution, managers must create visibility of the initiative's value. Users must make sure to state their needed degree of accuracy or quality of solutions in order to induce the right effort. Based on the map of characteristics provided by this research, managers can grasp the big picture of an initiative and understand success factors, potential hazards, and key areas to monitor such that corrective actions can be taken.

While these implications are verbalized towards the manager executing the initiative, there are characteristics which are hard for him to reach and get information about. Thus, any member of an initiative's project team is encouraged for awareness of characteristics on the map and to point out potential fallacies. This emphasizes the necessity of domain knowledge in Analytics initiatives and the immediacy to assure knowledge exchange between Analytics and domain experts.

In addition, this research raises attention to the complexity of Analytics, which cannot be mastered by "hiring some data scientists". Further, while Analytics initiatives require short organizational distance between Analytics experts and application domains of solutions, they may not require collecting all data from partners if Analytics solutions can be collected instead. Collaboration of this kind, and the sharing of own Analytics results with partners might induce benefits such as the partners recognizing the value of sharing such information.

Finally, challenges and issues reappear across domains since many organizations are currently working on similar topics. Managers might consider innovation collaborations and mutual assistance on Analytics across domains with non-competing organizations, which can also induce new use cases. In particular, LSCM managers should explore collaborative use cases beyond operational efficiency, which could facilitate new business models and new sources of revenue.

3.5.3 Future research and Limitations

This research provides potential for future research to validate the model – the map of characteristics – with quantitative methods to get more accurate insights on the domains' conditions. In accordance to that, other domains could be investigated for their specifications of the characteristics.

Further research demands arise from the specific characteristics. For example, the need for accuracy in Analytics models and algorithms and factors influencing this need could be studied further for break-even points of investment versus utility. This research could help managers to make better decisions by avoiding too high accuracy without utility from it but immense resource consumption or, in reverse, too little accuracy with serious consequences. Further, if hype and pain points release budget in larger organizations, research is needed on how to support organizations with limited budget such as small and medium sized organizations. If these organizations perish due to their limited investment potential, competition is sustainably altered. Additional research potential lies in overcoming the barriers such as changing to a data-driven culture, non-integrated IT landscape, or unwillingness for data exchange between partners.

Further, this research has limitations. The deployed method of semi-structured interviews results in the theoretical model being subject to the individual experience of the interviewees and the initiatives they individually conducted and took part in. While this study has been limited to the perception of saturation and its results should thus be generalizable, a larger sample size could allow stronger conclusions. The diversity of interviewees could further be increased in two manners. First, the study included interviewees from Germany and the USA. While the characteristics are expected to be similar globally, interviewees from more countries could become involved. Second, this study intentionally covers an informed outside view on several domains by inquiring Data Analytics Companies but thus excludes the domain insight view, which experts avoid to share due to inability to compare their domain to others.

4 Archetypes of Supply Chain Analytics Initiatives – an exploratory study

While Big Data and Analytics are arguably rising stars of competitive advantage, their application is often presented and investigated as an overall approach. A plethora of methods and technologies combined with a variety of objectives creates a barrier for managers to decide how to act, while researchers investigating the impact of Analytics oftentimes neglect this complexity when generalizing their results. Based on a cluster analysis applied to 46 case studies of Supply Chain Analytics (SCA) we propose 6 archetypes of Initiatives in SCA to provide orientation for managers as means to overcome barriers and build competitive advantage. Further, the derived archetypes present a distinction of SCA for researchers seeking to investigate the effects of SCA on organizational performance.

4.1 Introduction

Even before data got their mainstream reputation of being the "new oil" of the 21st century predestined to shape the digital economy (Keen, 2012), the potential competitive advantages through data analytics had already been recognized (Davenport and Harris, 2007). To remain with this analogy, data analytics represents the refinery process turning raw data into competitive strength. Analytics in itself is not a leading-edge invention, but increased attention was recently triggered by developments in information technology (IT) providing new access to data, organizations' need for better and faster decision-making and recent big data and machine learning tools enabling new levels of insight for decision makers (Cao et al., 2015). The field of Logistics and Supply Chain Management (LSCM), has been identified as one early adopter and a long-term user of Analytics (Davenport, 2009). LSCM has been employing operations research approaches for decades und uses purpose-specific analytics tools for very particular problems. As it is concerned with effectively integrating suppliers, manufacturers, warehouses, and stores, such that merchandise will be produced and distributed to the customer with a satisfying service level and with minimal costs in the right manner concerning time, location and quantity (Simchi-Levi et al., 2003), the necessity for analytical approaches to achieve these efficiency goals is inevitable. A recent industry report underlines the long-term data affinity of the LSCM sector from a practical point of view and the potential of logistics operations generating the amounts of data needed to create value by using Analytics

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(Jeske et al., 2013). However, the report emphasizes untapped potential in improving operational efficiency, customer experience or creating new business models in the sector. The fit of LSCM and Analytics is favorable since the satisfaction of customer needs and requirements is a leading theme in LSCM (Christopher, 2011, p. 12) and the meaningful insight provided by Analytics is used to ensure rules and workflows strengthening satisfaction of needs and requirements (Bose, 2009).

Scholars and practitioners alike have provided evidence that advantages to performance can be achieved from the domain specific use of Analytics, which was termed "Supply Chain Analytics" (Holsapple et al., 2014; Souza, 2014). In research, several authors have investigated the effects of Supply Chain Analytics. Information system supported Analytics capabilities have been indicated to improve LSCM performance (2010) and Analytics tends to have a positive impact on LSCM performance with high dependency on the fit of Analytics investment and LSCM process maturity (2012). The positive effect of Analytics on LSCM was further suggested as context contingent, especially on planning processes (2014). Schoenherr and Speier-Pero (2015) provide a wide variety of perceived benefits including improved supply chain efficiency and decreased supply chain costs. Furthermore, several scholars call for more research on the topic (Waller and Fawcett, 2013; Wang et al., 2016).

On the practitioners' side, industry reports have shown high expectations towards Analytics in LSCM, especially for reducing inventory, risk and improving batch sizes. Among others, better customer service, higher efficiency and faster reaction to supply chain issues based on investments in Analytics have been reported (Pearson et al., 2014). Furthermore, the development of more customer-oriented value chains with lower logistics costs due to the rise of data and Analytics has been suggested (Opher et al., 2016). However, investments are somewhat reluctant (Schmidt et al., 2015) and industry reports show that only a few firms achieve excellent performance in Analytics concerning LSCM (Marchese and Dollar, 2015). The majority of firms are lagging or struggling with Analytics in LSCM (Thieullent et al., 2016) with managers reporting missing experience and lack of knowledge on how to apply Analytics (Ransbotham et al., 2016).

In the studies summarized above, Analytics is customarily considered as one overall concept while making conclusions on it or deriving potential value and utility although single examples with individual issues and diverse analytical techniques are considered. Especially single examples are used to highlight Analytics providing benefits (Trkman et al., 2010) or savings (Thieullent et al., 2016) thereby projecting the exemplary benefits to Analytics as a general concept or overall approach. What remains unknown are the different outcomes of different approaches in relation to their intentions and execution. Analytics is usually not subdivided further although it presents a wide field with different objectives, orientations, and perspectives without a unified definition (Holsapple et al., 2014). In our view, it is too wide of a field to assume that all reported effects can equally be applied on different Supply Chain Analytics Initiatives, all Initiatives having the same potential of providing value for an organization or all barriers appearing could be overcome in a single manner. The sole attempt to subdivide Supply Chain Analytics in extant research can be found in the framework for Analytics applications in LSCM (Hahn and Packowski, 2015), which focuses on off-the-shelf IT Systems and therefore ignores important aspects of Analytics as well as Initiatives which are not system-specific. To derive more sophisticated and reliable research conclusions on the effects of Analytics on LSCM, a distinction of Supply Chain Analytics approaches is needed. We propose a distinction of how organizations apply Supply Chain Analytics, by using clustering on 46 case studies on Supply Chain Analytics Initiatives considering intended problem to be solved, execution, techniques, and the resulting Analytics Solution. Thus, this research investigates patterns in the activities of organizations applying Analytics to business problems in LSCM and explores their endeavors and motivation to form archetypes of Initiatives with exclusive characteristics. The outcome of the Initiatives as well as alignment of outcome and intention is out of scope for research. Regarding MacInnis Framework of conceptual contributions, the goal of this study is differentiation (MacInnis, 2011). Thus, we will indicate how the identified archetypes are different, why this differentiation matters, and how they can be used further. The study is based on publications about manufacturing firms, retailers and logistics service providers applying Analytics in LSCM. The research questions therefore states: *How can Supply Chain Analytics Initiatives be distinguished?*

The obtained archetypes can provide guidance to managers for their individual issues, and points of references of other organizations' previous activities, and thus, reduces barriers to adopt Supply Chain Analytics in their own organization. The archetypes represent types that are designed to be most different from each other to support learning of managers and students about Supply Chain Analytics. However, the combination of characteristics of different archetypes in the creation phase of a new Initiative in an organization is not relegated but rather encouraged with an individual and specific goal and approach to be designed by the executing manager. For researchers, the archetypes form a framework to investigate the different effects of varying approaches.

The remainder of the article is structured as follows: Section 2 provides a theoretical background with the objective to explain the characteristics chosen to form the archetypes. Section 3 presents the methodology on how archetypes are formed using cluster analysis. Section 4 explains the suggested archetypes and discusses their impact. Section 5 concludes the article and section 6 provides final remarks.

4.2 Theoretical Background

In this section, we will summarize Analytics, Supply Chain Analytics and characteristics of Supply Chain Analytics Initiatives.

4.2.1 Analytics

Due to its novelty and evolving nature, a wide variety of definitions of Analytics exists. Holsapple et al. (2014, p. 134) reviewed many of them to develop a collective definition stating that Analytics is "concerned with evidence-based problem recognition and solving that happen within the context of business situations". This definition highlights two specific aspects of Analytics. The first aspect, problem recognition, indicates the experimental part of Analytics to achieve a goal which is uncertain and unclear in the beginning requiring further exploration (Viaene and Bunder, 2011), and thus identifying what the actual problem is. The second aspect, problem solving, indicates that the value of Analytics is solely provided if a model or application is deployed and used (Viaene and Bunder, 2011). This aspect of Analytics is emphasized prominently in the literature, often specified as making decisions and taking actions (e.g., Barton and Court, 2012; Bose, 2009; Chen et al., 2012; Davenport and Harris, 2007). Both aspects establish a clear distinction from data aggregation Initiatives like dashboards and reports.

Davenport and Harris (2007) presented the benefits of applying Analytics to improve internal processes or an organization's competitive position. They illustrated that achieving success with Analytics is not based on deploying software but rather on three categories of factors: organizational, human and technological capabilities. Organizational capabilities consider analytical objectives and processes, human capabilities consider skills, sponsorship and culture, and technological capabilities consider data availability and Analytics architecture. While the models and software are often in the focus of research in Analytics due to apparent presentation of insight into the specific opportunities of Analytics, scholars highlight all three stated capabilities as critical to develop and successfully use models and software (Bose, 2009; Sanders, 2014).

The models and software used in Analytics are commonly distinguished as being descriptive, predictive or prescriptive (e.g., Das, 2014; Hahn and Packowski, 2015; Holsapple et al., 2014). The meaning of descriptive analytics is twofold. On the one hand, it presents the summary of data to report and monitor (Hahn and Packowski, 2015). On the other hand, it describes root cause analysis used to gain insights about the underlying phenomenon or process (Provost and Fawcett, 2013; Spiess et al., 2014). Predictive analytics estimates unknown values based on known examples. Prescriptive analytics determines and, in some cases, subsequently automates actions or decisions to achieve an objective given current and projected data, requirements and constraints.

Due to recent technological advances, Analytics gained additional interest as "Big Data Analytics", referring to Analytics performed with Big Data, which has been reported to have a positive impact on firm performance (Akter et al., 2016). Big Data originates in data management issues with technology in the early 2000s due to high volume, velocity or variety of data (Laney, 2001), which formed the original three "V's" of Big Data. Big Data is momentarily under frequent academic investigation including an increase of "V's" (e.g., Akter et al., 2016; Fosso Wamba et al., 2015; Sivarajah et al., 2017) considering several issues with Big Data beyond the aspects of data management and without the need for advanced technologies like distributed storage and processing, like Variability, Veracity, Visualization or Value. However, three "V's" is a leading theme (Chen et al., 2012; Dutta and Bose, 2015; Sanders, 2014; Schoenherr and Speier-Pero, 2015; Spiess et al., 2014; Waller and Fawcett, 2013; Wang et al., 2016).

4.2.2 Supply Chain Analytics

Similar to Analytics, no unified definition of Supply Chain Analytics (SCA) exists, while rarely one is proposed. Souza (Souza, 2014, p. 595) describes it as "focus[ing] on the use of information and analytical tools to make better decisions regarding material flows in the supply chain". Waller and Fawcett (Waller and Fawcett, 2013, p. 79) propose a definition while describing the field as [L]SCM data science: "[…] is the application of quantitative and qualitative methods from a variety of disciplines in combination with [L]SCM theory to solve relevant [L]SCM problems and predict outcomes, taking into account data quality and availability issues." Incorporating aspects of both descriptions and the definition of Analytics (Holsapple et al., 2014), we propose to define SCA as follows: *SCA is concerned with evidence-based problem recognition and solving within the context of logistics and supply chain management situations*.

Consequentially, SCA is neither a single and clear step-by-step approach to solve supply chain problems nor limited to certain tasks and processes in LSCM. Souza (2014) systemizes and distinguishes several techniques by the type of Analytics and the SCOR processes affected. The origin of the list of techniques is not explained and it is not exhaustive. Furthermore, another attempt on systemization results for an investigation on in-memory technology used in LSCM by grouping in-memory software applications for LSCM and designing a framework for analytical applications (2015). By considering the type of Analytics applied, whether the concept is data driven or model driven and methodological requirements, off-the-shelf software applications with analytical capabilities used for LSCM functionalities were grouped into monitor-and-navigate, sense-and-respond, predict-and-act, and plan-and-optimize. However, this categorization ignores objectives, organizational aspects and human aspects. Finally, examples of potential applications of Analytics in LSCM were summarized from the perspectives of the user and the tasks (2013). In summary, scholars have stretched a wide range of applications of SCA with various use cases for different functionalities and users, providing evidence that SCA is too complex to evaluate its impact as a general concept.

The generalization has further impact on managers by creating barriers, which wewant to address with this study. Thus, this research focuses on barriers related to a missing understanding of how to apply SCA on individual problems of an organization and substantiate relevant SCA Initiatives. Sanders (2014) provides an extensive overview on barriers of Analytics in the context of LSCM and presents several barriers of which the following are related to the interest of this research. First, managers, especially in leadership positions, may not see the value provided by Analytics resulting in missing vision, understanding of the full capacity and how to change the organization to apply Analytics successfully. Second, so called analysis paralysis hinders organizations from applying Analytics because they cannot handle the overwhelming opportunities, the speed of technological change what results in the inability to define a starting point. Organizations may thus try to randomly analyze data for some eventual causation, some business units may optimize their sub processes with little global effect or organizations try to measure everything at once without understanding what to focus on. Third, instead of experiencing a lack of data, many organizations drown in data. Besides technological issues to handle these amounts of data, organizations do not know how to leverage the existing data capability and how to base decisions on it.

4.2.3 Dismantling Supply Chain Analytics Initiatives

This subsection describes the characteristics used to analyze SCA Initiatives to form archetypes. We identified 34 characteristics in an extensive review of Analytics literature which are presented in six categories. The characteristics and categories are presented in Figure 12. Drawing on Chae et al. (2014), we consider SCA Initiatives as (one time) projects aiming to achieve supply chain objectives using evidence-based problem solving and recognition with a focus on inducing process redesign, tool development or long-term process changes like automation or continuing decision support.

First, the reasoning behind any Initiative should be a shortcoming in a supply chain objective (SCO). Either because there is a deficiency in comparison to the theoretic potential or because higher performance is aspired. In the literature, several frameworks of performance dimensions indicating supply chain objectives are proposed (Ambe, 2013; Bowersox et al., 2007; Chan, 2003; Gunasekaran et al., 2004) without one being unanimously accepted. Several operational metrics reappear in most frameworks we investigated, but the categorization differs tremendously. The following objectives have been elaborated based on a review of these frameworks: *cost* (SCO1), *quality* (SCO2), *time* (SCO3), *flexibility* (SCO4), *sustainability* (SCO5), *innovativeness* (SCO6), *customer relationship* (SCO7) and *supplier reliability* (SCO8).

Second, we return to the concept of core capabilities of an analytics competitor: organization, humans, and technology. The organizational aspects can be represented by the analytics objective (AO) of an analytics Initiative. In accordance with Manyinka et al. (2011) and Holsapple et al. (2014) we identified six analytics objectives. Based on evidence-based approaches these include the creation of *transparency by democratizing data* (AO1), *the identification of root causes* by experimentation (AO2), the *evaluation of business performance and environment* (e.g., efficiency or risk assessment) (AO3), the *segmentation of populations* (including products and services) (AO4), the *support and replacement of human decision-making* (AO5), and the *development and innovation of new sources of revenues* (e.g., business models, products or services) (AO6). In a given Initiative, the fulfilment of one objective can be necessary to pursue a consecutive

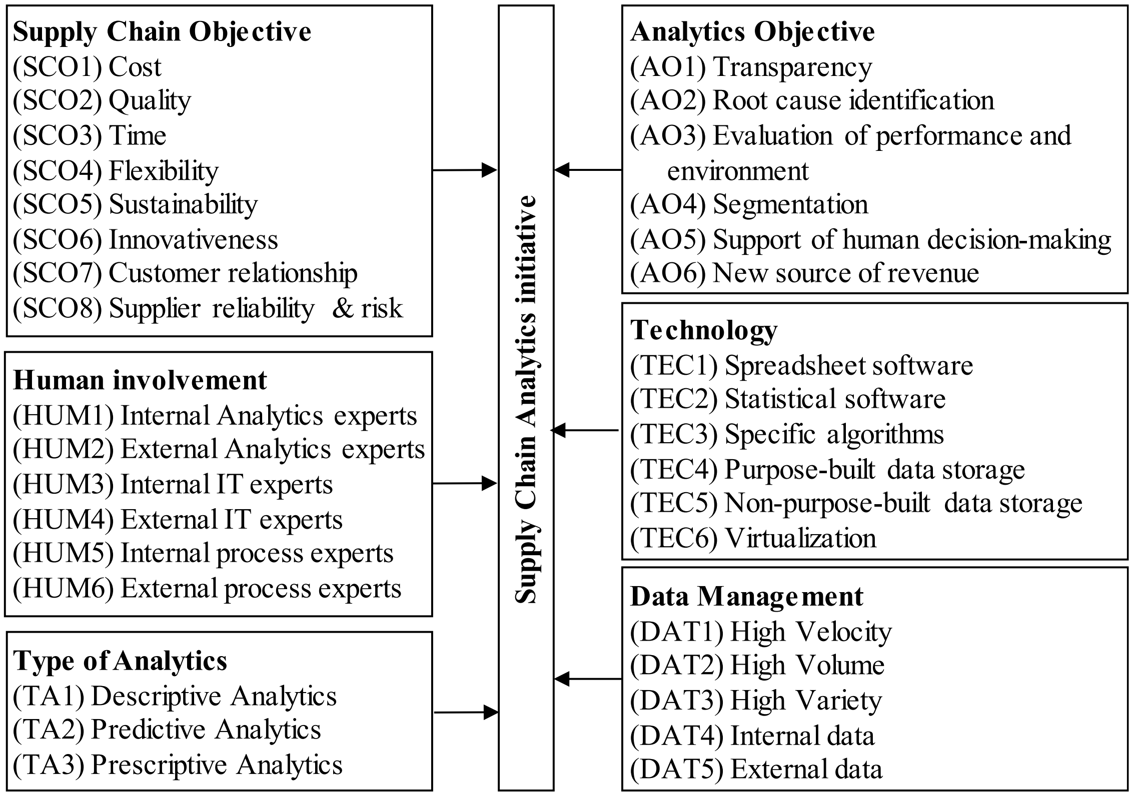

Figure 12: Characteristics of a Supply Chain Analytics Initiative

objective. For example, a transparent business process may be necessary for further analytics approaches leading to supported decision-making.

Third, going forward with analytics capabilities, the human involvement (HUM) in a specific Initiative can be incorporated by distinguishing the business functions bringing expertise into the Initiative. Considering Davenport and Harris (2007), Bose (2009) and Dietrich et al. (2015) we identified several specific roles in analytics Initiatives (e.g., several roles from providing access to data to the data management as well as business function from user to sponsor of the Initiative) which can both be internal to the organization or externally contracted. We aggregated the roles leading to three groups and six roles: *internal analytics expert* (HUM1), *external analytics expert* (HUM2), *internal IT expert* (HUM3), *external IT expert* (HUM4), *internal business process expert* (HUM5), *external business process expert* (HUM6). As we have seen in our analysis, external and internal expertise is not mutually exclusive. Depending on the complexity of the Initiative, organizations combine available expertise in various forms to achieve success.

Fourth, for the technological (TEC) aspects and final capabilities the infrastructure can be a major barrier (Sanders, 2014). However, Davenport and Harris (Davenport and Harris, 2007) direct the focus on tools and analytics architecture. They identify small and short Initiatives done with *spreadsheet software* (TEC1) which can be applied by analytical amateurs. Analytical professionals however will either use *statistical software* (TEC2) for experimental purpose or *define and refine specific analytical algorithms* (TEC3) building new and often purpose-specific tools. We distinguish the last two, since this algorithm might be bought from a third-party vendor. On the other hand, Davenport and Harris (2007) discuss the importance of data storage and access. However, since their initial work, the field has seen significant developments. Opposed to statistical software models gathering data from existing systems or sending it to a third-party to execute the analytics methods, the classical mode is a *newly purpose-built data storage* (TEC4). Recently, the concept of a *non-purpose-built data store to gather data from* (TEC5) is emerging following the idea of creating a single storage for analytical purposes to be defined later. This concept is often called "Data Lake" (Fang, 2015). Finally, the concept of virtualization, as prominently known due to cloud computing, allows *access to analytical methods and results disconnected from the actual data infrastructure* (TEC6), e.g., with mobile devices (Kambatla et al., 2014).

Fifth, data management (DAT) for analytical purposes can face serious challenges demanding supplementary effort (Laney, 2001). As explained above, the big data concept represents serious data management challenges, which we have thus incorporated into the evaluation. This includes a *high velocity* of data (DAT1) being analyzed or collected, a *high volume of data* (DAT2) to be included in Analytics and a *variety of data sources, data structures and data semantics* (DAT3). Further, besides *internal data* (DAT4), managers are supposed to be creative about the inclusion of *external data* (DAT5) sources (Barton and Court, 2012).

Sixth, reconsidering the works of Hahn and Packowski (2015), and Holsapple et al. (2014), the type of analytics (TA) can be *descriptive* (TA1), *predictive* (TA2), *prescriptive* (TA3) or several of them at once due to chaining or combination.

As mentioned in the introduction, the Initiative's outcome has been neglected in the analysis process. The outcome, which is presented in a percentage or absolute value for savings or improvements in a monetary value, time or quantity is highly dependent on the individual case, organization and industry. Thus, it was not considered meaningful for the derivation of archetypes. Additionally, this research aims to recognize what organizations aspire, the intention and the consequential execution in a qualitative manner. Quantitative outcomes do not fit this aim. We further omitted firm size and organizational form, since our interest is in the Initiatives presented by single projects, which can be a relative small size compared to the size of the organization due to the intention to solve a small problem.

No characteristic described above is mutually exclusive and some will correlate since the presence of one characteristic may likely demand the presence of another.

4.3 Methodology

To identify SCA Initiative archetypes, we used the machine learning method of clustering. Clustering is a descriptive or explorative data analysis technique which relies on interpretation by the analyst based on insight into the original data (Kaufman and Rousseeuw, 2005). This fits MacInnis (MacInnis, 2011) requirement to use analytical reasoning for facilitating the aspired differentiation. Below, we present the data collection, analysis, and evaluation process.

4.3.1 Data Collection

Since this research considers case studies from organizations, research databases did not provide a sufficient source. Based on the insight we gained from the publications presented above we used key words and synonyms of Analytics[1] as well as Analytics Objective (see section 4.2.3) in combination with LSCM[2] to conduct an extensive search via the google search engine (with customized search results deactivated). Besides case studies from organizations, we identified several third-party websites, software and solution vendors and organizations applying Analytics, as well as news websites, expert websites and blogs which we further used for snowball sampling. Finally, we approached organizations for cases. In total, we identified a shortlist of 49 Initiatives with promising information richness to evaluate their characteristics.

4.3.2 Data Analysis

To identify archetypes, we looked at previous research similar to our intent. [L]SCM archetypes aimed at providing managers with understanding about organizational adaptation and performance evaluation have been identified by non-hierarchical clustering on supply chain IT and organizational structure variables (2008). The variables were collected via a survey including variables such as B2B e-commerce supply chain integration, ERP applications, operational centralization as well as market and financial

[1] (“Data Science”, “Business Intelligence”, “Big Data” or “Data Mining”)

[2] (“transport*”, “operation management”, “deliver*”, “value chain”, “warehous*”, “supplier”, “resource planning”, “inventory”, “material flow”, “product handling”, “distribut*”, “shipping”)

performance. Supply chain integration archetypes were investigated to understand the relationship between integration and performance and to provide parsimonious descriptions useful for discussion, research, and pedagogy as well as to reveal insight into the underlying structure (2010). Survey based collection of variables of customer integration, supplier integration, internal integration, business performance and operational performance and the data analysis with hierarchical and subsequent non-hierarchical clustering determined the archetypes. The authors briefly describe five archetypes with three balanced integration archetypes and two customer-leaning integration archetypes in different nuances. LSCM job type archetypes were deviated from collected job descriptions from a major employment website to provide suggestions on how training and professional development should occur (2010). Text analysis was used to mechanically code the job descriptions and hierarchical cluster analysis using Ward's method was applied to identify eight archetypes. Concluding, clustering has proven as research method in LSCM to identify archetypes with the method adapted to the individual dataset. Thus, focusing on clustering as the method for our research is supported by previous LSCM research.

We used the 34 characteristics of SCA Initiatives discussed above as binary measures to systematically describe the found Initiatives. Two researchers coded the cases independently. The cases were coded from the perspective of the analytics result's final user and with the supply chain objective focused on the value creation process. If a case provided inconclusive evidence for a variable, the information was sought from the organization or the case was rejected. Thus, three of the shortlisted case studies were rejected. Both researchers discussed the coding regularly to align the interpretation of the variables. After coding, each difference was discussed and resolved by consensuses. The researchers calculated Cohen's Kappa as 0.65 (Cohen, 1960), indicating a substantial agreement on the scale of Landis and Koch (1977).

As the collected data is binary, common methods to determine dissimilarities between two objects such as computing the Euclidean or Manhattan distances cannot be employed. To deal with this type of the data, the approach proposed by Kaufman & Rousseeuw (2005) building on an adapted version of the similarity coefficient defined by Gower (1971) was used to calculate the dissimilarity matrix. All variables were treated as asymmetric binary as they did not represent the presence or absence of a characteristic

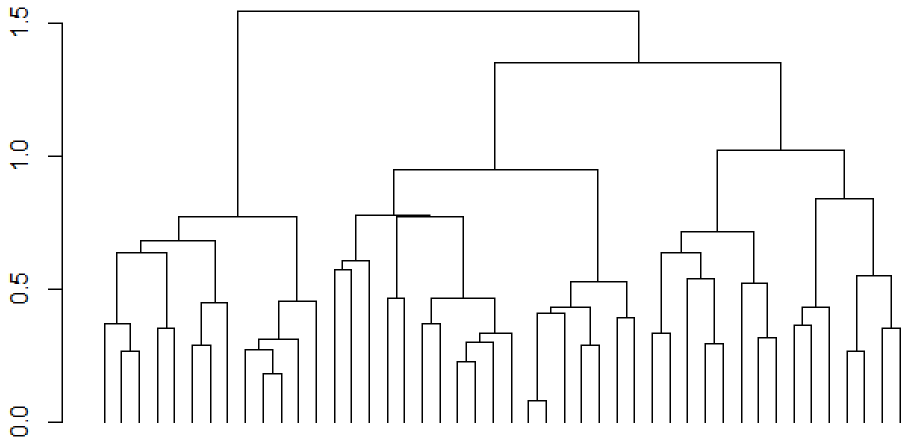

Figure 13: Dendrogram of Cluster Analysis with Ward's method

but the presence and non-presence due to missing evidence for presence (Faith, 1983), thus leading to adaptions of the distance measurement. We used the statistical software ‘R’ to perform the clustering and its evaluation.

We decided for hierarchical clustering due to the advantage of visually inspecting the agglomerations via a dendrogram. We tested UPGMA, Ward’s method, complete linkage and WPGMA and evaluated the dendrograms by outlier influence due to late agglomerations of single observations. The most promising method in our evaluation has been Ward’s Method visualized in Figure 13. During the process, we had to omit (DAT_4), since every case relied on internal data. As Hair et al. (2010) point out, there is no completely objective way to determine the number of clusters and the final choice remains to the researcher. However, the researcher shall be guided by his research objective. Since we want to create reasonable clusters while keeping them conceptionally knowledgeable and insightful, we limited our considerations to a maximum of eight clusters and decided for the best number of clusters in that range based on several criteria: The change in agglomeration distances between merging clusters peaks at the changes from three to four clusters and from five to six clusters (non-consecutive intersections). Based on the dendrogram, six clusters represent a reasonable cut-off. The Dunn index (Dunn, 1973) is maximized for five clusters, while the index remains constant for six and seven clusters. The Silhouette index (Rousseeuw, 1987) suggests seven clusters with six clusters as second best and five clusters as third best choice. As shown in Figure 14, the difference between five and six clusters is more pronounced than that between six and seven clusters. We decided for six clusters, since it is the visually most reasonable, once amongst the best and once the second best considering the indexes. In the visual

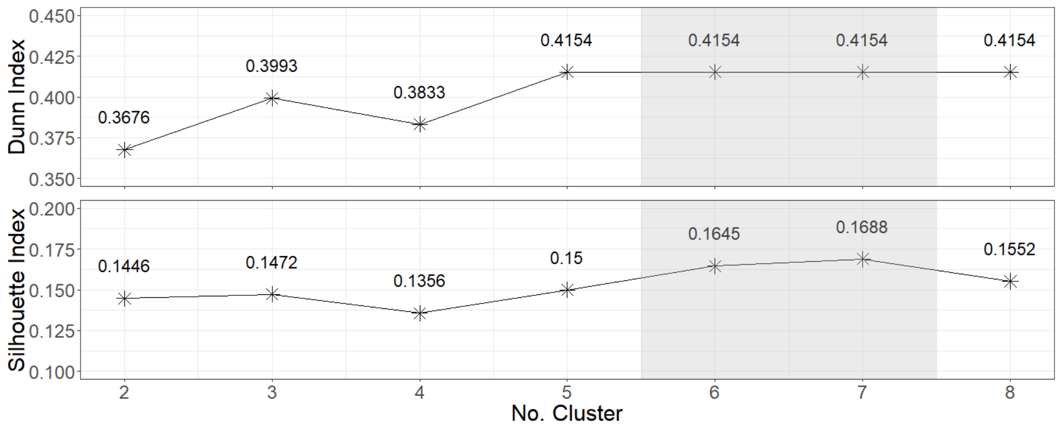

Figure 14: Cluster Evaluation (best evaluated in grey)

evaluation, we took into account the changes in distance from five to six cluster or six to seven not being consecutive intersections. The resulting six clusters were interpreted by considering the Initiatives in each cluster and by comparing the averages of variables amongst clusters.

4.4 Results and Discussion

In this section, we describe the six found clusters by highlighting characteristics and combinations of characteristics of the Initiatives in each cluster in comparison with the Initiatives in the others. The findings therefore present the researchers' interpretation. All Initiatives within a cluster were then analyzed together to extract commonalities. Clusters have been named to underline their major traits. The results are visualized in Figure 15 with key points for every characteristics category in the order presented in section 4.2.3.

4.4.1 Cluster 1 – Educating

The Initiatives in the Educating cluster focus on gathering data (sources) new to the organization and process, that are used as more advanced input in the decision-making of the LSCM process to improve output but will not lead to process redesign. This cluster contains mainly forecasting Initiatives with the specific goal of providing the right amount of goods without storing excess inventory or having stock-outs such that the consumer of goods is served best (e.g., the use of data on weather, income, historical sales or regional marketing campaigns to determine inventory allocation to individual stores). Thus, the objective is to improve process quality and customer relationship. The tools used in these Initiatives are dominantly predictive and aim to produce more precise inputs for decision-making in consecutive processes of inventory allocation. In some Initiatives, no evidence on how the consecutive processes are further affected by the tool can be

Educating the LSCM process by including new data (sources) as process input for improved process output...

SCO *to* improve quality of process output and subsequent customer relationship
AO *by* improving human decision support
HUM *with* external Analytics experts and mixed IT and process teams, *who*
TEC implement models or specific algorithms in existing systems (existing in the unchanged process), *and*
DAT introducing (new) external data
TA *using* predictive techniques

Observing of LSCM process conditions indicating causes for process deficiencies based on newly gained process insight…

SCO *to* (insightfully) improve quality of the process and its costs
AO *by* identifying (data-based) causes of quality deficiencies and providing evaluation means based on causes
HUM *with* mixed teams of experts, *who*
TEC use statistical tools to create purpose-built tools (attached to existing systems or stand-alone), *by*
DAT analyzing internal data with high volume and variety
TA *using* predictive techniques

Refining LSCM process by faster, broader, and more frequent guidance for workers or decision makers to act on…

SCO *to* improve costs and reduce time of actions based on process innovations
AO *by* providing human decision support
HUM *with* mixed teams of experts but strong internal expertise, *who*
TEC create purpose-built tools combined with new storage systems, *for*
DAT analyzing data with high velocity and volume
TA *using* prescriptive techniques

Alerting LSCM process owner automatically on indicators of pre-defined critical conditions and events…

SCO *to* improve various objectives
AO *by* providing (knowledge-based) means of (automatic) evaluation, triggering decision support on alert
HUM *with* mixed teams of experts, *who*
TEC create purpose-built tools (attached to existing systems or stand-alone), *for*
DAT high velocity data analysis
TA *using* descriptive and predictive techniques

Advancing the LSCM process and/or business model based on newly gained process data availability and insight…

SCO *to* change and thus improve the process, and its quality and create innovations
AO *by* providing (data-availability-based) transparency and causes to enable (formerly unavailable) evaluation and decisions
HUM *with* (mostly) internal experts, *who*
TEC create (stand-alone) purpose-built tools connected to data storages without predefined purpose ("data lakes"), *by*
DAT analyzing data with high velocity, volume and variety
TA *using* descriptive techniques

Investigating LSCM process and asset deficiencies to identify causes and enable creativity and engineering design based solution search…

SCO *to* improve costs and quality of processes and assets
AO *by* identifying causes
HUM *with* mixed teams but strong external Analytics expertise, *who*
TEC apply statistical tools, *for*
DAT analyzing internal data
TA *using* descriptive techniques

SCO – Supply Chain Objective
AO – Analytics Objective
HUM – Human involvement
TEC – Technology
DAT – Data Management
TA – Type of Analytics

Figure 15: Proposed Supply Chain Analytics archetypes (no chronology or sequence intended)

found. The report on one Initiative specifically states that this is intended, since employees shall use the output of the model – the prediction – and not question it. The focal organization usually buys a custom- built or customized advanced tool or system extension developed by external Analytics experts, which includes external data sources new to the forecasting organization and combines it with internal data from existing systems to integrate it with these systems.

4.4.2 Cluster 2 – Observing

The Initiatives in the *Observing* cluster concentrate heavily on predicting LSCM process deficiencies in the short-term or medium-term future with a newly developed tool observing and monitoring the processes gain reaction time to either prevent the deficiencies or enable counteraction. The prediction is based on process conditions indicating the definitely identified in the Initiative. Thus, observing indicates watching with knowing what to pay attention to. The supply chain objectives are mixed but tend to focus on cost reduction and quality improvement. The process is sought to be improved by observing and avoiding identified causes of quality deficiencies but not essentially by changing or redesigning the process. The Initiatives in Cluster 2 describe a variety of data experiments to improve process accuracy and quality (e.g., identifying production quality indicators that have to be monitored, estimation of product weight based to package weights to sequentially use package weight as quality indicator for correct items, identify influencing factors on punctuality of arrival to adjust plans when factors are present). In a distinct proportion of Initiatives, the maintenance process of an asset, machine or vehicle, was under investigation. The actors in the analytics team are mixed from internal and external experts for Analytics and IT. Process experts are usually in house. The software used includes spreadsheets – the cluster contains the only Initiative the authors could identify using spreadsheet software (in combination with statistical software) – and statistical software but no specifically designed algorithm. The techniques used are primarily predictive and analytically aimed at anticipating the behavior and evaluating the performance of a process as well as understanding the causes of the process behavior. Thus, they usually exploit patterns in the data opposed to process knowledge as in *Alerting* Initiatives. Data is either stored in purpose-built data storages or gathered from existing systems. In addition, cloud computing was used in some Initiatives to provide access to the automatically evaluated processes to facilitate monitoring. External data is barely used, but internal data comes in high volumes and variety to create sophisticated process insight tools.

4.4.3 Cluster 3 – Alerting

The Initiatives in Cluster 3 use similar approaches as the Initiatives of Cluster 2. However, the product of the Initiative diverges with Cluster 3 Initiatives aiming to produce a support system for process owners. These are supposed to call for attention or alert in certain, especially critical, process conditions or events, which are mostly predefined rather than identified. Critical refers to negative process effects or possible loss of revenue. The on-demand attention contributes to meet various supply chain objectives including cost reduction, quality improvement, flexibility increase or customer relationship improvement. The LSCM process is usually untouched, as opposed to *Advancing* or *Refining* Initiatives, while the monitoring task of the process is reduced from active checking to passively getting alerted on actions required (e.g., by providing alerts when delivery vehicles do not progress on route as has been estimated which demands modification of routes, informing receivers or parallel deliveries with faster delivery time). To achieve this, the Initiatives repeatedly describe teams of internal process experts teaming up with mixed experts in analytics and IT. The need for external assistance in these Initiatives may be attributed to the desired output, which is to develop a dedicated software tool in all Initiatives in Cluster 3. These tools perform monitoring tasks of a specific process and recommend actions for improvements (e.g., to lower energy consumption, to increase flexibility, to reduce cost, to improve utilization of capacity) as well as request needed actions (e.g., change routes, change active supplier, maintain machines, to adjust prices). Thus, high velocity of data analysis is in focus. The organizations in some cases used the tool to offer new services to their customers. The tools usually need their own purpose-built data storage with virtualization technologies commonly used for improved access. Further, they are likely to include external data sources necessary for risk assessments of suppliers, sources of delays on routes or condition evaluation supported by additional manufacturer provided data. As opposed to *Observing* Initiatives, these Initiatives are commonly driven by process knowledge of critical conditions and therefore focus on finding data-driven ways to automate what process owners were actively monitoring before. The Initiatives use and combine descriptive and predictive techniques to summarize data for monitoring and extrapolating future conditions.

4.4.4 Cluster 4 – Advancing

The Initiatives in Cluster 4 focus on advancing a process, or even the organization by developing new business models. Thus, as opposed to *Observing* Initiatives, which optimize reacting on process conditions potentially leading to process quality deprivation, or to *Alerting* Initiatives, in which known conditions require actions, these Initiatives usually introduce process changes in the form of adjusted process steps that were identified based on process data made available to create this transparency – the large scale data availability is often seen as major progress and benefit with resulting tool focused process execution. This cluster unites Initiatives of organizations with a certain maturity in Analytics. These usually bring internal expertise into the Initiative from all relevant areas and only occasionally require external expertise. In particular, the Initiatives aim to achieve data availability and transparency and subsequently understand the focal process (e.g., by equipping assets with a variety with sensors and mobile devices, collecting data, and analyzing data from similar assets together to determine the life cycle process of a machine and its components or routines of transport vehicles performing deliveries and consequentially creating a new form of predictive maintenance contract with customers). In this context, "understanding" not only refers to the continuous evaluation of processes, but also to the use of descriptive techniques for causal analysis to identify process parameter settings and combinations causing losses in process quality, and to provide a decision support to counteract these losses. The Initiatives integrate data with high velocity, high volume and high variety. To achieve this, purpose-built software tools are developed. The results of the analysis lead to tools for process monitoring combined with decision support systems. These Initiatives further emphasize the collection of data without predefined purpose, with prospective use of these centralized data in future analyses. The tools and select data are regularly made available to customers to create a competitive advantage for their own products.

4.4.5 Cluster 5 – Refining

The Initiatives in cluster 5 aim to squeeze the last bit of untapped efficiency out of a system by refining processes with assisting or rather guidance functions for human operatives to reduce costs and save time. Additionally, these Initiatives have a strong focus on creating an innovative advantage over competition. To achieve this, prescriptive techniques are used to determine the best course of action – redesigning the process with manifold interactions with the system to guide decision-making by human operatives. This includes the transfer of routing algorithms to pickers and the stops of their carts in distribution centers, augmenting delivery vehicle drivers with routing algorithms dynamically using real-time traffic conditions to re-optimize while the vehicle is already on the road or extending manufacturing processes with real-time quality evaluation to change the production sequence. Thus, as opposed to the archetypes above, the focus diverges from understanding and monitoring a process to continuously adjust (or refine) it. To achieve the aspired goal, a high volume of high velocity data must be analyzed by purpose-built tools. The highly customized tools as well as the systems developed to execute these tools are developed in-house with a combination of internal and external expertise.

4.4.6 Cluster 6 – Investigating

The Initiatives in cluster 6 are united by the investigation of causes of deficiencies or rather major process flaws. Thus, the objective of these Initiatives is to increase process quality and reduce costs by identifying and mitigating the root causes of process flaws or finding proxies to enable monitoring them (e.g., identify shelf replenishment flaws by monitoring check-out patterns in super markets to identify patterns of lost sales or identifying critical sensor signals presenting factors causing quality issues in production processes). The important aspect to distinguish this cluster from the others is the consequences taken when a root cause is found. Handling the root causes in the Initiatives could not be done by automating decision-making or more sophisticated monitoring. Rather, the cause of process reliability or deficiency has to be handled by changes in new product development, major process redesign or changes in materials demanding creativity and engineering design. These Initiatives usually combine external Analytics with mixed external and internal IT and processes expertise. Identifying causalities is supposed to start a solution search instead of automating evaluation or continuous decision support, as compared to *Observing*, and *Alerting* or *Refining* Initiatives. The results of the Initiatives are based on statistical software with a focus on internally available data. Purpose-built data storage systems are created.

4.4.7 Discussion on Archetypes

The clusters presented above present archetypical Initiatives of Analytics in LSCM. The identification and interpretation of core characteristics of clusters was conducted to highlight the uniqueness of each archetype and present archetype diversity in intended problem to be solved, execution, techniques, and product. Single Initiatives forming the clusters and therefore determining the archetypes differ in some characteristics from the archetype. Thus, new Initiatives may be created with differences in single features but with a clearer understanding of archetypical feature combination. In addition, while there is some (expected) overlap of clusters, we consider it as new insight that e.g., the same Analytical objective may be used to pursue different Supply Chain objectives.

Considering the identified archetypes, as well as the characteristics forming the clusters, we observed that the type of Analytics did not dominate. While the *Refining* archetype consists solely of optimization Initiatives, optimization techniques could be found in the *Educating* and *Advising* archetypes as well. Predictive techniques can be found in all archetypes, including the *Refining* archetype, since techniques were usually combined in more sophisticated Analytics Initiatives. This holds true for descriptive Initiatives as well. While the type of Analytics has been our greatest concern, we additionally conducted an analysis for dominating characteristics by evaluating all characteristics across all archetypes in search for characteristics present in all Initiatives forming an archetype but not present in any other archetype. However, we could not find any characteristic fulfilling this condition of dominance. To extend our analysis of critical characteristics, we considered whether the supermajority (two-thirds) of Initiatives possessing a certain characteristic are given in any archetype. This condition was defined as weak dominance for this research. This condition was fulfilled by the features SCO8, TEC1 and TEC5. However, these features have two, one, and three observed Initiatives possessing the characteristic, respectively. Therefore, we did not consider these features as critical. Concluding, we are confident in our results not being dominated by one single characteristic.

When presenting these results to scholars, a major point of controversy has been, whether the archetypes present levels of Analytics maturity of an organization which we reject after careful consideration due to the following aspects: First, considering the given data, one Initiative does not reflect the whole organization but a business unit executing the Initiative. This is consistent with research indicating Analytics should follow process maturity (Oliveira et al., 2012) or rather additional Analytics Maturity should fit process maturity (Trkman et al., 2010) which is therefore not necessarily leveled across the organization. Second, organizations could execute Initiatives of lower maturity since it may still provide benefits and Initiatives of higher maturity using external support. Thus, an Initiative is not a distinct confirmation of an organizations capabilities. Third, in the Initiatives considered, two organizations have been observed twice and one organization three times. The Initiatives thus spread across archetypes with the seemingly more mature Initiatives either in the same year or earlier. Fourth, research has pointed out, that the objective of an Analytics Initiative is often set without the consideration of the complexity of the Analytics required (Viaene and Bunder, 2011). While the objective guides the Initiative, the necessary Analytics maturity may be determined during the execution and not before and thus not influence the Initiative. However, we acknowledge that the level of internal expertise involved may indicate the business criticality.

Concerning an Initiative perspective, this actually opposes maturity models setting standards for organization-wide implementation for highest maturity (Wu et al., 2016) or considering strategic Initiatives for highest maturity (Wang et al., 2016). These levels of maturity address the analytics culture of the organization (Davenport and Harris, 2007) which may influence the spread of Initiatives but not dictate the choice of Initiatives.

Finally, we learned that, in order to achieve value with SCA, the solution does not have to be an organization-wide expensive third-party tool. Small models build with R or SPSS and visualized with Tableau can provide significant value already.

4.4.8 Discussion on overcoming barriers with archetypes

This research aspires to provide means to overcome barriers of applying Analytics to LSCM related to a missing understanding. Considering Sanders (2014), we chose and summarized several barriers relevant for this research in section 4.2.2.

Lack of leadership is indicated to be caused by lack of vision, lack of understanding of the capability, and the lack of understanding how to lead change. The latter, also described as creating a data-oriented culture (Kiron et al., 2012) or data-driven culture (McAfee and Brynjolfsson, 2012), is considered a key competency for managers to transform organizations to sophisticated Analytics capabilities and beyond the scope of this research. The lack of vision is addressed by the core concepts of each archetype since they are supposed to guide vision by providing points of reference to individualize, adapt and combine. The lack to understand the capabilities required to apply Analytics is addressed by the characteristics of Analytics Initiatives emphasizing structure of and resources needed for executing an Initiative. However, it has been suggested that the existence of these capabilities in an organization doesn't guarantee the ability to bring it to full use (2014).

The barriers of lacking objectives are addressed by the generic objectives presented by the two objective characteristics categories, and by the specific objectives provided in the archetype descriptions. This highlights to managers the necessity of defining an objective as compared to the "poking" for correlation as described by the notion of analysis paralysis. Defining an objective which Analytics should answer is a valuable starting point (Lavalle et al., 2011). The archetypes further emphasize that Analytics Initiatives should not bedriven by the latest and most innovative technology but by technology fitting the purpose of the identified objectives.

Further, as evident from the discussion above, with an orientation on objective-driven SCA with subsequent choice of data, managers should not drown in data. The archetypes further present the opportunity of relying on external guidance for choosing the necessary data. In addition, it is indicated that using non-Big Data can still achieve benefits. This is further underlined by process models for Analytics Initiatives recommending data collection to be a later step in the project (e.g., Dutta and Bose, 2015; Provost and Fawcett, 2013). Even while drowning in data, having the right data to successfully execute the Analytics Initiative is not guaranteed.

4.5 Conclusion

In our research, we investigated how SCA Initiatives can be distinguished. Literature suggests reluctance of LSCM to invest in Analytics Initiatives caused amongst other reasons by managers missing ideas in how to approach SCA. With our research, we address this shortage by providing a distinction of Initiatives providing knowledge to managers about typical approaches to use SCA to gain business value. Based on the patterns emerging form a cluster analysis of 46 SCA Initiatives we propose six archetypes that show considerable differences in how organizations deploy SCA. In the analysis, the problem to be solved, execution, techniques, and resulting Analytics Solution of the Initiative have been considered. In detail, we examined characteristics necessary to execute an SCA Initiative and therefore display areas that have to be taken into account by managers designing new Initiatives. The characteristics are aggregated into the following groups:

- Supply chain objective that shall be addressed which represents the problem or deficiency in the LSCM process;
- Analytics objective, which is addressing how data and Analytics are supposed to support, effect or change the LSCM process;
- Human expertise in areas relevant to the Initiative as Analytics, IT and the LSCM process (and how it is sourced);
- Applied software and hardware for analytical tasks and deployment of developed solutions and tools;
- Data sources and characteristics;

- Applicated types of Analytics (and subsequently analytical methods)

Regarding the groups of characteristics above, our findings support considerable differences in Initiative archetypes. The patterns identified allow us to answer the research question: SCA Initiatives can be distinguished in the six clusters which are described in regard to the characteristics in subsection 4.4 as well as LSCM process centric as follows:

(1) *Educating:* The LSCM process remains as existing but will be enhanced with new data (sources) information as process input to improve decisions to be made during the process resulting in enhanced LSCM process output quality and customer orientation. This typically emerges as improved tool used in the process like a new forecasting model in a product allocation process or new forecast model for a risk evaluation process.

(2) *Observing:* The LSCM process is extensively investigated for conditions that indicate process deficiencies or issues in the short-term or medium-term future with a resulting tool to monitor the process based on the newly gained insight. The knowledge about the conditions improves process quality and costs due to earlier reaction. Examples include detection of engine vibration patterns enabling maintenance planning of vehicles such that a repair shop is the final stop of a route on a suitable point in time instead of random breakdown far away from access to maintenance, or detection of weather patterns resulting in traffic and road conditions demanding changing of routes. However, identified conditions are indications and leave room for human decision-making.

(3) *Alerting:* LSCM process owners are provided with alerts on critical conditions and events that immediately demand reactions. The conditions are usually known by process owners without the need of analytical identification and certain in their negative impact on the process demanding actions. Alerting Initiatives' central task is making the necessary data available to automate the alert as opposed to repeated human check-up actions. Examples include alerts on closed roades for vehicle routing or automated recommendations of price changes and acceptance of shipments for cargo airlines in close to departure time-windows. Here again, the LSCM process is typically supported but not altered.

(4) *Advancing:* The LSCM processes and business models will be advanced by enabling changes due to insight made available with intense data collection and analysis. Large scale data collection is central to the Initiative, using sensors and mobile devices to create data-availability-based transparency and evaluation of LSCM process steps. The insight

is used to improve process quality by changing process steps under incorporation of the insight and creating analytics driven innovations replacing process steps as well as making insight available to interested third parties as business model innovation. Examples are machine profiles allowing determination of accurate predictive maintenance processes which can be sold by the machine manufacturer to the machine user, or driver profiles to create new monitoring steps to reduce idle time. These Initiatives differ from *observing* and *alerting* by extensiveness of data collection and analysis typically demanding big data technologies, and range of the resulting tool, which changes the process to become tool and thus data focused as opposed to a minor process support.

(5) *Refining:* The LSCM processes are changed to incorporating faster, broader, and more frequent guidance on actions and decision support. Instead of optimized plans that are executed, the objective of these Initiatives is to optimize plans during execution dynamically based on data about current events and conditions. Examples are dynamic changes of routes of vehicles already on the road, or dynamic changes of picker routes in distribution centers already picking. The LSCM process is changed due to extensive focus on guidance tools guidance during process execution.

(6) *Investigating:* The LSCM process (and asset) deficiencies and issues are investigated for their causes to enable the solution search for design changes to the process. These changes are supposed to create new processes with improved costs and quality over the process under investigation. As opposed to issues described in *advancing* or *refining*, process changes like automation or data-driven tools for guidance will not create control over the process issues addressed in these Initiatives. Thus, creativity and engineering design is required. Examples include the investigation of occurrence of empty shelf space in retail stores to redesign replenishment processes of products or the investigation of process environment factors in production lines leading to quality issues that have to be avoided.

4.5.1 Theoretical Contribution

Our research contributes to LSCM research with a focus on SCA and the practical application of SCA, an area that has been demanded to be investigated by several researchers in LSCM (Sanders, 2014; Schoenherr and Speier-Pero, 2015; Waller and Fawcett, 2013). The identified archetypes provide an empirically developed taxonomy. Further, they give insight into the underlying structure of Analytics Initiatives used in

LSCM – why and how they are applied. The research decomposes SCA Initiatives in important distinct parts, which can structure future research. Thereby, this research specifically addresses characteristics influencing Analytics Initiative and is not limited to distinction by software (Hahn and Packowski, 2015) or LSCM process (Souza, 2014).

The proposed archetypes seek to guide discussions, research and training of students becoming managers enabled to use SCA. The discussion aspired by the authors should address how to enable organizations to create Initiatives beyond the presented contemporary archetypes with more sophisticated supply chain and Analytics objectives, rather than conducting single case studies or literature reviews on the competitive impact without empirical evidence. Our research provides a framework supporting the investigation of the effects of different types of Analytics Initiatives and helps researchers working with data models and quantitative case studies to orientate themselves in the bigger picture of their research. This framework further allows to investigate the implications of various kinds of SCA Initiatives on performance, barriers as well as the efficiency of the Initiatives based on the archetype of the Initiative. Finally, this research gives a two-dimensional picture to introduce students to this field and ease the process of understanding important factors and possibilities by the proposed first dimension of archetypes to understand what companies do and the second dimension of characteristics of SCA Initiatives to understand what aspects to consider when constructing an Initiative. Thus, it enables researchers and students to introduce their LSCM knowledge into Analytics Initiatives and provide considerable value that is required for successful Initiatives (Schoenherr and Speier-Pero, 2015; Waller and Fawcett, 2013).

This research further addresses the gap between theory and organizational activities highlighted by several scholars, especially in management science (Banks et al., 2016; Suddaby, 2010). Our archetypes map the activities of organizations and provide templates for organizations and scholars in the field to understand what drives organizations to their activities.

4.5.2 Managerial Contribution

This research copes with the managerial barriers related to missing insight into the application of SCA. By describing archetypes of this application, we give managers directions for future SCA Initiatives based on their initial business situation, available means and objectives. Presenting the results to experts in Analytics, the archetypes were well received with the remark that managers may lack creativity of how to address business problems with Analytics which could be supported with the results of this research. In this regard, managers may combine archetypical approaches to create new Initiatives or explore Initiatives with supply chain or analytical objectives rarely observed.

Considering the barriers discussed in section 4.4.8, our research presents how the application of SCA creates value for an organization and how decisions are made based on SCA. Managers should be enabled to decide which of the overwhelming opportunities provided by SCA to take and which to postpone or reject with the primary objective of providing value to the organization. Naturally, this requires the creativity to design new Initiatives.

The research further provides a framework for managers to understand the key components to build an SCA Initiative. First and foremost, an Initiative has to address existing problems – meaning any disparity between objective state and actual state – for the LSCM Part as well as they require an analytical objective to address the LSCM problem. Further characteristics display fields that have to be developed and improved over time to design more complex Initiatives, even in the same archetype. For the Human category, that includes building skills supporting the execution of Initiative as hard skills in Analytics as well as communication skills to transfer thoughts, ideas and experience between the different experts. In the technology category, this include investments in easier data exchange, faster analysis and calculation as well as more-powerful analytical tools. In the data category, this includes broader data collection and higher standards for data quality.

Our research further develops a vocabulary to communicate managers' objectives and vision while highlighting small but crucial differences. The archetypes are imagined as a menu of options a manager may use to choose specific or combined items. We intend the archetypes to guide his Initiative design process, as opposed to having an infinity of options that quickly becomes overwhelming. Therefore, besides providing directions, the archetypes also serve as validation of the fit of characteristics of the Initiative and thus, it's practicality. This enables managers to pinpoint what they aspire and communicate it directly and properly.

The other way around, the archetypes can be stimulation for two additional types of managers keen to use Analytics in LSCM. First, Managers that achieved some routine in Initiatives of a specific archetype may get stuck in that archetype and repeat it for ever new use cases which eventually leads to decreasing marginal value from that kind of Initiatives. Second, managers the are supposed to “make more from their data” – a type that is not very rare from our personal experience. Both types of managers could, using the archetypes, identify promising problems to address and subsequently search for interested users or rather “problem owners”. The first type obviously benefits over the second from knowing eventual problem owners from her previous projects she could address again with another beneficial Initiative.

4.6 Final remarks

4.6.1 Limitations

Due to the various sources of the Initiatives considered, their descriptions are provided in various levels of detail regarding the characteristics used to evaluate them. With 46 cases, the amount of considered cases is low. Additionally, the observed cases only represent successes since these are more likely to be published in any form. Unsuccessful cases to use Analytics in LSCM could not be identified. Further, the cases have been collected in a procedure which is hard to recreate. This is due to the lack of a public database for such case studies, especially considering the amount of studies needed to conduct a meaningful cluster analysis. Since databases for research (e.g., Scopus, Web of Science or EBSCO) did not yield relevant results, we were reliant on an open search platform. The search was suspended when a reasonable amount of time (16h / two workdays) for searching cases did not yield any new results. However, the possibilities to collect the data for this research were rather limited.

Furthermore, considering the data analysis, the decision about the number of clusters and thus the number and structure of the identified archetypes depends on several vague factors and cannot be made objectively. The clusters are created based on the researchers’ interpretations and judgement. We presented the results to researchers in LSCM and experts in Analytics, which assessed the clusters as reasonable.

4.6.2 Future Research

This study takes a step towards understanding the inner structure of a growing field of research, which should not be investigated as a single entity to generalize use, effects and benefits anymore. Thus, future research may investigate the effects of SCA Initiatives distinguished by archetype to create more sophisticated insight. The archetypes may also be correlated to Analytics maturity or the growth-share matrix to identify easy-to-start archetypical Initiatives for organizations with low maturity and identify factors of successful Initiatives with the potential to create competitive advantage. Additionally, since we consider this research to be contemporary, we encourage to repeat this research in five to ten years.

5 Explaining the Competitive Advantage Generated from Analytics with the Knowledge-based View – The Example of Logistics and Supply Chain Management

The purpose of this paper is to provide a theory-based explanation for the generation of competitive advantage from Analytics and to examine this explanation with evidence from confirmatory case studies. A theoretical argumentation for achieving sustainable competitive advantage from knowledge unfolding in the knowledge-based view forms the foundation for this explanation. Literature about the process of Analytics initiatives, surrounding factors and conditions, and benefits from Analytics are mapped onto the knowledge-based view to derive propositions. Eight confirmatory case studies of organizations mature in Analytics are collected, focused on Logistics and Supply Chain Management. A theoretical framework explaining the creation of competitive advantage from Analytics is derived and presented with an extensive description and rationale. This highlights various aspects outside of analytical methods, including cross-functional teams, iterative problem solving with user feedback, solution consumability, and innovative culture. Further, this study presents a practical manifestation of the knowledge-based view.

5.1 Introduction

The use of Analytics is increasing across industries. It is fueled by trending concepts like big data and data science, innovative technologies such as distributed computing and in-memory databases, as well as the rapid increase of data available for processing. A recent survey showed a constant increase of organizations perceiving the role of Analytics as critical, a closing maturity and capability gap between digital natives and traditional companies in applying analytics, and its strategic role, as embodied in appointments of C-level executives for Analytics (Alles and Burshek, 2016). A large proportion of surveyed organizations believe that they can gain competitive advantages from Analytics. Another study goes as far as to suggest that data-empowered organizations may threaten the market survival of companies not using these approaches (FreshMinds, 2015). However, organizations also struggle with adopting Analytics successfully (Viaene and Bunder, 2011), with one difficulty being the ongoing discussion about what defines Analytics. Holsapple et al. (2014) investigated a plethora of definitions of Analytics,

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including the definition by Davenport and Harris (2007), who initiated the broader recognition of Analytics with their famous book. Holsapple et al. (2014) identified at least six definitional perspectives on Analytics just in the literature they reviewed, highlighting the diverse comprehension of the topic. Based on the core characteristics of Analytics, it has been described as recognizing and solving business problems based on evidence such as data, facts, but also well-reasoned estimations. Further, Analytics initiatives are diverse and have to fit with people, processes, and tasks to enable their benefits (Ghasemaghaei et al., 2017), demanding investigation of which practices and conditions lead to generation of competitive advantage from Analytics.

Competitive advantage is frequently discussed in the strategic management literature. The resource-based view argues for competitive advantage based on the resources of firms, including assets, capabilities, processes, attributes, and knowledge – if these are rare, imperfectly imitable, and non-substitutable (Barney, 1991). The capability-based view emphasizes these resources as the capabilities of firms that cannot be purchased on the market and require strategic vision to develop over time through the strategic decisions of bounded rational managers facing uncertainty, complexity, and conflict (Amit and Schoemaker, 1993). The relational view argues that firms' resources are of limited value in providing competitive advantage, and instead credit it to the combined resources of a network of firms (Dyer and Singh, 1998). Finally, the knowledge-based view narrows down the resource required to provide competitive advantage to firms to just one item, which satisfies all the necessary characteristics – the knowledge held by the individuals of the firm (Grant, 1996a). Managers are responsible for integrating and applying that knowledge. As the integration and application process of knowledge fits the definition of Analytics as problem recognition and solving, the knowledge-based view provides a reasonable theoretical grounding to investigate the generation of competitive advantage from Analytics.

One discipline increasingly adopting Analytics is Logistics and Supply Chain Management (LSCM). Scholars expect Analytics to change how supply chains operate (Schoenherr and Speier-Pero, 2015). In practice, executives assess Analytics as playing a pivotal role in driving profit and creating competitive advantage in LSCM (Thieullent et al., 2016). Due to the vast number of applications areas and the assumed potential, a sub-discipline of Analytics used in LSCM has formed, labeled SCM Data Science (Waller and Fawcett, 2013) or Supply Chain Analytics (Chae, Olson, et al., 2014; Souza, 2014).

LSCM is considered an early adopter of analytical methods, using Operations Research to optimize inventories, locations, and transportation costs (Davenport 2009). Holsapple et al. (2014) even cite an article on production control and automation while exhibiting the origins of Analytics. In recent research, the use of Analytics has shown a positive impact on LSCM performance (Chavez et al., 2017; Sanders, 2016; Trkman et al., 2010) and researchers have called for further research on Analytics in LSCM (Schoenherr and Speier-Pero, 2015; Waller and Fawcett, 2013). However, research has also shown that a major proportion of organizations remain reluctant to use Analytics or are not even familiar with it, due to, amongst other factors, lack of ideas about how to achieve advantage from it (Sanders, 2016; Schoenherr and Speier-Pero, 2015).

To investigate Analytics' impact on organizations' competitive advantage, narrowing the focus is necessary. This article's investigation focuses on the example of LSCM for several reasons in addition to the field being an early adopter and achieving considerable value from employing Analytics. From its core characteristics, LSCM is driven by efficiency and cost-effectiveness (Simchi-Levi et al., 2003), which demands sophisticated decision-making – as supported by Analytics. Therefore, it is not surprising that LSCM has a long history of emphasizing data-driven decision-making (Souza, 2014; Waller and Fawcett, 2013). LSCM is usually a complex task, managing information, products, services, and financial and knowledge flows across internal units such as procurement and manufacturing, as well as between globally dispersed organizations including suppliers, retailers, or manufacturers (Bowersox et al., 2007). Consequently, collaborative approaches to Analytics are needed, presenting a unique challenge for Analytics, since data comes from several different organizations and results are deployed across them (Davenport, 2009). In addition, LSCM is a human-centered process with a variety of decision makers acting on the basis of their personal experience, resulting in unexpected events, human errors, and consequential dynamic effects in the processes (Wang et al., 2014). Wang et al. (2014) further highlighted the diversity of processes and the resulting heterogeneity of process knowledge. In summary, LSCM is chosen as a focus due to the field's experience with data-driven solutions, the constant demand for further improvement, and the challenges associated with adopting Analytics given the complex, diverse, dispersed, and error-prone processes distributed across several business units, organizations, and decision makers.

Considering the impact of Analytics, the objective of this research is to investigate how organizations can generate competitive advantage from Analytics. For this purpose, Analytics' dependency as inputs not only on data, but also domain knowledge, is acknowledged (Provost and Fawcett, 2013), consequently leading to activities in a specific domain like LSCM being more similar to each other as compared to activities in a different domain. In research, this results in domain-isolated chains of references, since scholars tend to reference scholars from the same domain (Holsapple et al., 2014). Thus, in order to create coherence of research and to narrow the focus, empirical evidence will be collected from organizations maturely employing Analytics in a LSCM context. This leads to the following research question: *How is competitive advantage generated from Analytics in context of Logistics and Supply Chain Management?*

The remainder of this article is structured as follows. Section 2 reviews the knowledge-based view and literature on Analytics to establish a link between them, as embodied in the propositions formulated for this research. Section 3 documents the research design, for which confirmatory case studies have been chosen. Section 4 discusses the results, with a focus on the proposition of creating an extensive explanation of how Analytics generates competitive advantage. The research will be concluded in Section 5, which provides implications, limitations, and indications for future research.

5.2 Theoretical Background

In this section, Analytics activities are mapped onto the argumentation for competitive advantage from the knowledge-based view (KBV) to present their congruence. The connecting points are summarized in ten propositions.

5.2.1 Knowledge-based view

The KBV explains the generation of sustainable competitive advantage from knowledge, summarized in the following section. Regarding knowledge, its creation, transfer, and integration are distinguished as follows: *Creation* refers to development of new knowledge. *Transfer* indicates sharing of knowledge without implying that the receiver gains the ability to apply it. In contrast, *knowledge integration* describes the sharing of knowledge such that receivers can apply it, but without necessarily possessing it.

5.2.1.1 The source of knowledge-based competitive advantage

An organization ("firm") cannot use the open market as a source of sustainable competitive advantage (Barney, 1986, 1991). Instead, according to the resource-based view, it must create such advantage from its resources, which need to be rare, imperfectly imitable, and non-substitutable.

Developing from the resource-based view, scholars have created several other argumentations. These include the KBV, which establishes the knowledge possessed by organizations as their most essential resource for competitive advantage (Conner and Prahalad, 1996; Grant, 1996a, 1996b). It is based on an emphasis of the strategical value of knowledge in organizations (Kogut and Zander, 1992; Teece, 1981; Winter, 1987) and differentiating the performance of organizations using asymmetries in knowledge (Conner and Prahalad, 1996). In the KBV, the role of individuals is underlined. Organizational members carry, generate, and preserve the knowledge, while integration of knowledge for its application is governed by managers of organizations. Neither holding knowledge without integration nor the attempt to integrate non-existing knowledge can be a source of competitive advantage (Grant, 1996b). Thus, the KBV also deals with issues of organizational coordination and structure (Grant, 1996a).

The aspect most essential for the knowledge integration and application is the degree of its transferability (Grant, 1996a), which depends on its form: explicit or tacit (Grant, 1996a; Kogut and Zander, 1992; Teece, 1998; Winter, 1987). Perfectly explicit knowledge is easy to articulate and communicate, transmittable without loss of integrity, and observable, consumable, learnable, and usable with insignificant marginal costs (Grant, 1996a; Kogut and Zander, 1992; Winter, 1987). In contrast, perfectly tacit knowledge is difficult to articulate; not completely transferable in substance and meaning; and costly to transfer since it is tied to skills and experience-based intuition, revealed by application and acquired through practice ("know-how") (Grant, 1996b; Kogut and Zander, 1992; Nonaka and von Krogh, 2009; Teece, 1998). These forms exist on a continuum indicating some degree of tacitness in almost all knowledge (Spender, 1996). For organizations, this distinction implies the need for different actions to exploit the knowledge (Teece, 1998).

Tacitness of knowledge is substantial in the argumentation for generating competitive advantage from knowledge unfolded by Grant (1996b, 1996a), Spender (1996) and Teece (1998) and was followed repeatedly (Alavi and Leidner, 2001; Purvis et al., 2001; Vachon and Klassen, 2008; Zack, 1999). Due to tacitness, knowledge as a resource can be scarce, non-transferable, and non-replicable. This denotation, adapted from the relevant conditions of the resource-based view, equally describes how access is denied to competitors. Organizations possess such knowledge, which resides in specialists who gain it through learning and knowledge creation (not further explained by scholars), but which cannot be communicated completely or easily and cannot be converted to utility without the support of other individuals (Demsetz, 1988). Based on Demsetz (1988), the KBV argumentation suggests higher outcomes from several specialists combining their knowledge and rejects a "jack-of-all-trades". However, the knowledge must be put into action for competitive advantage. Thus, Spender (1996) and Grant (1996b, 1996a) conclude that organizations' managers must guide organizational members to execute complex, team-based productive activities resulting in the combination of their knowledge, making it possible to apply that knowledge during the value creation process of transforming input to output. Thereby, the combination represents knowledge integration with inimitable organizational capabilities as the outcome.

For knowledge integration into the value creation process, Grant (1996a) identified four mechanisms that several scholars have elaborated (Canonico et al., 2012; Heugens et al., 2004; Hurnonen et al., 2016; Spanos and Prastacos, 2004): (1) Rules and Directives, (2) Sequencing, (3) Routines, and (4) Group problem-solving and decision-making. They aim to integrate the knowledge efficiently, defined as effectively integrating while minimizing the transfer, which is dependent on process characteristics, division of tasks between individuals, and organizational design (Grant, 1996a). These mechanisms,

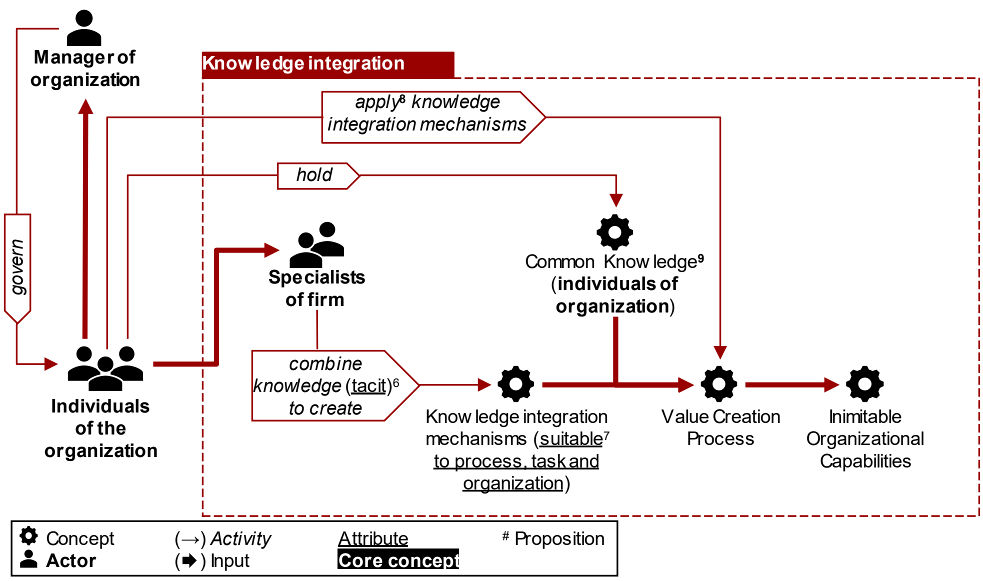

Figure 16: Knowledge integration illustrated

especially the first three, can be rather impersonal, communication minimizing, and knowledge transfer economizing (“automating” or “programming”) (Alavi and Leidner, 2001; Grant, 1996a; Hurnonen et al., 2016; Spanos and Prastacos, 2004; Van De Ven et al., 1976). In contrast, lateral relationships that are personal, less straightforward, and interaction-dependent can be deployed, as in the fourth mechanism (Canonico et al., 2012; Galbraith, 1973; Grant, 1996a). In accordance with dependence on different process and organizational characteristics, mechanisms must be suitable for varying complexity, uncertainty, or importance of tasks (Grant, 1996a; Hurnonen et al., 2016; Spanos and Prastacos, 2004). Knowledge integration is illustrated in Figure 16, with numbers referring to the propositions introduced later in this chapter.

The outcome of knowledge integration depends on the knowledge all individuals of an organization share due to their affiliation to the organization, since knowledge integration is catalyzed by this common knowledge (Grant, 1996b, 1996a; Spender, 1996). An organization’s internal knowledge, combining specialized and common knowledge with knowledge integration mechanisms, cannot be accessed by competitors. Thus, they are not able to use the same organizational capabilities and, hence, cannot achieve the same value created by tangible resources in the value creation process of transforming input to output. Provided these organizational capabilities are advantageous over competitors’ capabilities, the competitive advantage depends on the efficiency of knowledge integration. The efficiency relies on (1) the level of common knowledge, (2) the frequency and variability of integration of common and specialized knowledge, and (3) structures that economize the communication needed for knowledge integration.

Grant (1996b, 1996a) further discusses the conditions leading to sustainable competitive advantage. Its sustainability requires continuous renewal of organizational capabilities, accomplished by two actions: (1) extension of existing capabilities to include new types of knowledge, and (2) use of existing knowledge in new capabilities. Solely executing either one of the actions may not be sufficient. As a result, the sustainability of the competitive advantage is dependent on increasing the scope of knowledge integration continuously. The conditions for sustainable competitive advantage are illustrated in Figure 17.

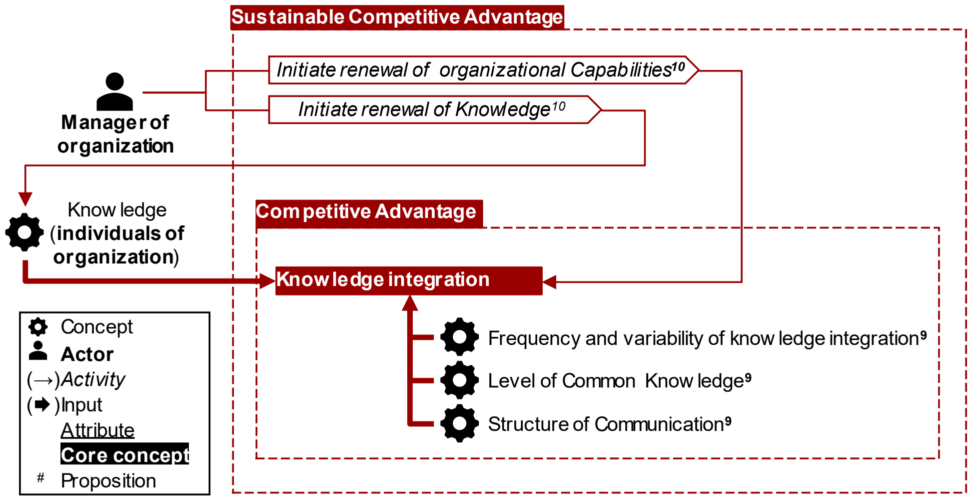

Figure 17: Sustainable competitive advantage from knowledge illustrated

5.2.1.2 The problem-solving perspective on the knowledge-based view

For the KBV, as described above, scholars both pointed out deficits and introduced extensions to cover originally unconsidered aspects. One of these aspects is the disregard for knowledge creation, which Grant (1996a) himself had already evaluated as serious. Nickerson and Zenger (2004) developed their extension to the KBV to cover this aspect based on solving valuable problems – subsequently referred to as the problem-solving perspective (PSP).

The PSP addresses two deficits of the KBV. First, the KBV does not explain efficient creation of knowledge. The PSP argues for solving valuable problems to create desired knowledge with value assessed by the expected value of the problem's solution and organizational capacity to profitably achieve the solution. Second, the market's irrelevance as a source of knowledge in the KBV is argued to be inaccurate in the PSP, resulting in the introduction of forms of solution search with varying levels of market inclusion. Scholars have also revisited the PSP with regard to managerial innovation, development, and improvements topics (Choo et al., 2015; Hsieh et al., 2007; Jeppesen and Lakhani, 2010; Macher, 2006; Tiwana, 2008). Regarding these topics, knowledge creation must be organized efficiently and effectively by solving valuable problems rather than exploiting existing knowledge. The value of a problem depends on the value viable solutions can provide and the costs of identifying the solutions (Nickerson and Zenger, 2004). Thereby, effectiveness and efficiency in problem-solving result from generative problem solving, based on learning and reflection (Choo et al., 2015). In contrast, symptomatic problem solving, which focuses on controlling the potential of negative outcomes – "fixing" a problem – does not contribute to knowledge creation and may affect existing knowledge negatively.

The value of problems and their solutions in the PSP builds on Simon's (1962, 1973) study of complex systems. He argues for a problem's generic concept being a goal state that is produced from an initial state (Simon, 1962) and solving being a sequence of processes that must be discovered to get from initial state to goal state. The complexity of problems increases with increasing number of parts – knowledge sets needed for the solution (Jeppesen and Lakhani, 2010) – that interact in a non-simple way. Complex problems possess characteristics providing potentially valuable solutions and are resultingly valuable (Nickerson and Zenger, 2004). Further, problems vary by the definition of their structure. This definition represents an abstract degree of how well the nature, substance or patterns of a problem are understood and known (Simon, 1962). The definition of a problem locates it on a continuum between an ill-structured and well-structured state (Simon, 1973). A problem is well structured if practical effort for solution search is allowed by the existence of a problem space in which goal state, current states, attainable state changes, and acquirable knowledge about the problem including a reflection of external links can be represented with complete accuracy. Existence implies access to relevant knowledge sets on the structure due to knowledge possession or transfer, although this may be limited by the knowledge's tacitness. The development of a problem definition – discovering the various parts of the problem space – is argued to be the solution search (Simon, 1973). Once the definition applicable to a problem is complete, it can be used for other occurrences of the same problem, because unknown knowledge set interactions are revealed and mastered such that the ill-structured problem has changed to a well-structured one. How to solve it is now understood (Jeppesen and Lakhani, 2010; Macher and Boerner, 2012).

The solution search consists of selective trials which uniquely combine chosen knowledge and which are distinguished by their directional nature and heuristics (Nickerson and Zenger, 2004; Simon, 1962). Directional search uses prior experience about positive and negative outcomes and reinforces the search in the direction leading to positive outcomes – "trial-and-error" – which is more suited for low knowledge set interactions since it is prone to remain enclosed in a local solution area (Gavetti and Levinthal, 2000; Hsieh et al., 2007; Nickerson and Zenger, 2004). In contrast, heuristics are premised on beliefs about linkages between choices and actions, resulting in fewer

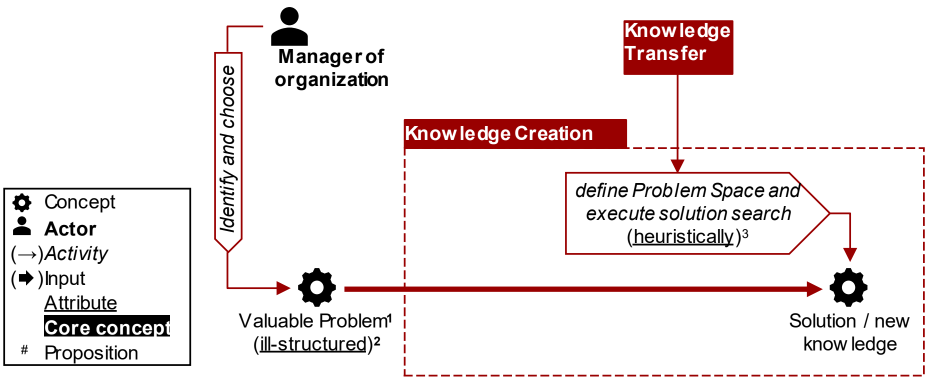

Figure 18: Knowledge creation illustrated

trials and selection of relevant knowledge sets based on anticipated interaction, which is more suited for problems with high knowledge set interactions but also requires increased knowledge transfer (Gavetti and Levinthal, 2000; Nickerson and Zenger, 2004). The knowledge creation process is illustrated in Figure 18.

To execute the ideal solution search, the relevant knowledge sets' interactions need to be identified. To identify non-simple knowledge set interactions for solution search requires a group of individuals holding relevant specialized knowledge, which develops common cognitive maps limited by human cognitive constraints (Nickerson and Zenger, 2004). The likelihood of creating new knowledge from combining knowledge sets increases with the diversity of the knowledge sets, while the difficulty of knowledge transfer also increases (Jeppesen and Lakhani, 2010; Tiwana, 2008). A mediator bringing some degree of knowledge set redundancy to the group could enhance knowledge brokering, translation, and interpretation but has been argued to provide no benefit beyond that (Tiwana, 2008). Further, marginal knowledge sets, which are distant from conventional approaches to a problem but close enough to have insight on its problem space, can be beneficial to the solution search by introducing approaches that are unconventional to the rest of the group (Jeppesen and Lakhani, 2010). Assessment of both the ideal solution search and solution is the task of the manager, including gaining understanding of the problem space, identifying relevant knowledge sets and selecting a group of their holders, and choosing a governance mode for the solution search, leading to eventual knowledge acquisition (Nickerson and Zenger, 2004).

The PSP describes three modes of governance, which vary in control over the solution search in terms of centralization and market inclusion, and extent of knowledge transfer (Nickerson and Zenger, 2004). Costs for knowledge transfer are higher for solution searches outsourced to the market, since the community within organizational boundaries

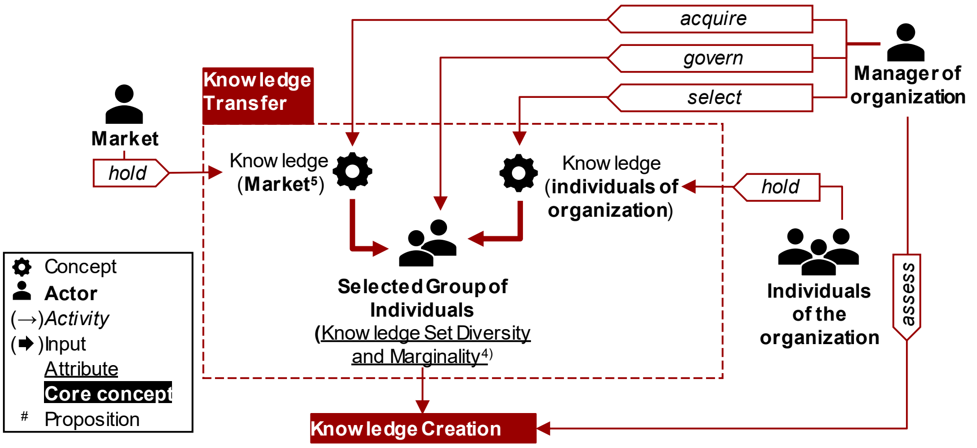

Figure 19: Knowledge sources and transfer illustrated.

can create a common communication framework, which can even enhance knowledge creation for ill-structured problems (Hsieh et al., 2007; Macher, 2006; Macher and Boerner, 2012; Nickerson and Zenger, 2004). Hence, the market approach is suited for well-structured problems with lower knowledge transfer but higher chance of exploiting a more efficient incentive system. However, it also creates access to more diverse knowledge sets and new solutions with superior performance, justifying higher costs (Jeppesen and Lakhani, 2010). In contrast, the knowledge transfer advantages of internal solution search are more suited for ill-structured problems. The sources of knowledge sets and their transfer are illustrated in Figure 19.

5.2.1.3 Synopsis of the knowledge-based view

Nickerson and Zenger (2004) theorize that an organizational manager's generation of valuable solutions to valuable problems can be expected to, for example, enhance and develop products and services, and reduce costs of production or delivery. Hence, they represent novel knowledge that can be combined with existing knowledge and integrated into the value creating transformation process of inputs to outputs, leading to a more advantageous output. To facilitate this integration, managers must assess the value of the solution and realize its integration with mechanisms described in the originating KBV. Hence, the PSP extends the KBV, which describes the integration of knowledge to generate competitive advantages, by explaining the creation of the necessary knowledge. The KBV and the PSP are illustrated in Figure 20.

5.2.2 Analytics

Analytics creates knowledge, makes it usable, and benefits from it, supposedly resulting in a competitive edge (Davenport and Harris, 2007). Thus, the KBV and Analytics show

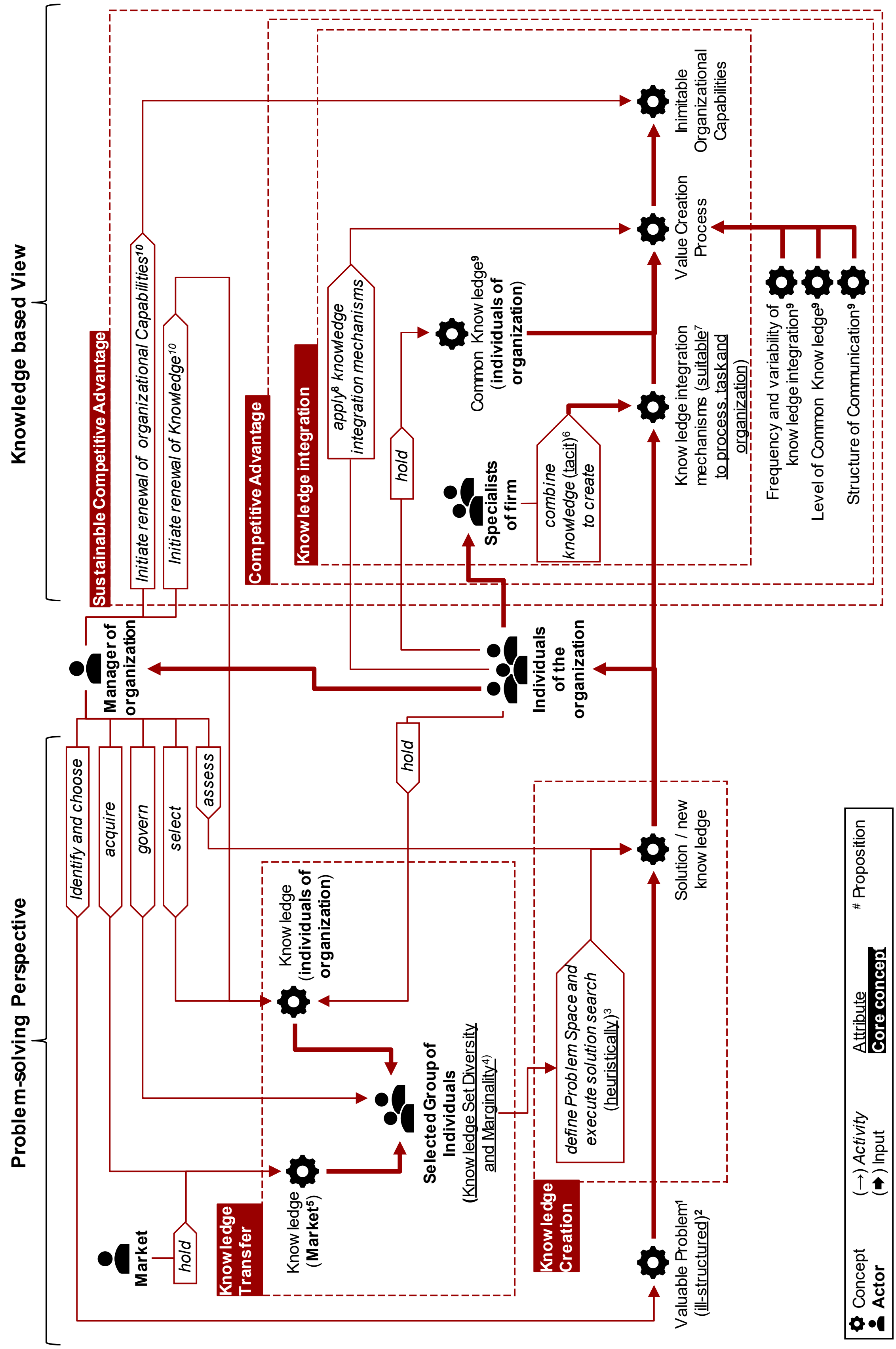

Figure 20: Visualizing the knowledge-based view

a high degree of agreement at the macro level. The following section explores aspects on which the KBV and Analytics agree on a more granular level.

While the concept of Analytics is still subject to debate, similar to Larson and Chang (2016) and Holsapple et al. (2014), this study acknowledges related concepts such as business intelligence, big data, and data science as intertwined with Analytics. A vague distinction is of Analytics being focused on decision support in business processes, business intelligence being either an overarching term or the provision of information, big data being a technological advancement, and data science being advanced models and algorithms, but this distinction cannot be applied consistently and each concept draws from or depends on the others. With the decision support focus, which demands the integration of analytical insight into a process, Analytics displays the most relevant and leading concept for this research.

5.2.2.1 The process of Analytics initiatives

Holsapple et al. (2014, p. 134) provide a meta-definition for Analytics, which is "concerned with evidence-based problem recognition and solving that happen within the context of business situations". Hence, solving a problem is at the core of Analytics initiatives and should be the starting point of an Analytics initiative, since it is a requirement for creating usable and valuable solutions, and it is a manager's task to identify this problem (Barton and Court, 2012; Bose, 2009; Marchand and Peppard, 2013). More specifically, "problem" can also be labeled business objective (Seddon et al., 2017; Viaene and Bunder, 2011), business question (Bose, 2009; Larson and Chang, 2016), or an opportunity to exploit (Barton and Court, 2012). Absence of this predefined purpose is indicated to result in a waste of resources, creating skepticism towards Analytics rather than data-driven improvement (Lavalle et al., 2011).

Thus, Analytics is endorsed for a focus on handling modern complexity such as dynamic interrelationships and increasing complexity of market and organizational activities, and for challenging established business practices, with extraordinary requirements for precision, accuracy, and speed (Holsapple et al., 2014; Kiron et al., 2012, 2014; Marchand and Peppard, 2013). Further, complexity originates from extensive information and data flows (Beer, 2018; Bose, 2009) or uncertainty (Viaene and Bunder, 2011). This requires technically complicated analytical methods with uncertain suitability to the problem and the involvement of various, interacting specialists (Carillo, 2017; Davenport and Harris, 2007; Viaene and Bunder, 2011).

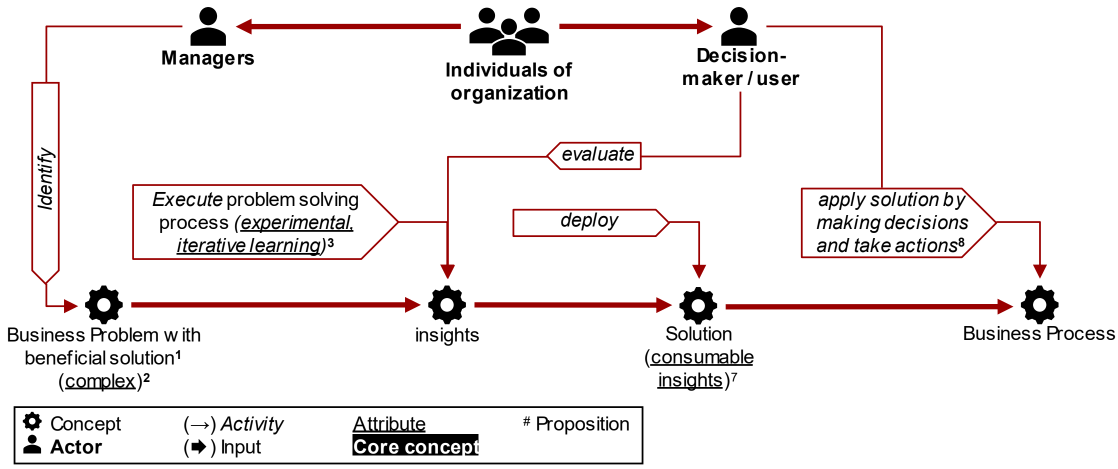

Figure 21: The process of Analytics initiatives illustrated

The process for solving these complex problems is described as exploratory and experimental. Based on initial planning, the process consists of well-designed experiments and iterative learning, changing the course of actions due to insights gained (Bose, 2009; Carillo, 2017; Larson and Chang, 2016; Marchand and Peppard, 2013; Viaene and Bunder, 2011). Hence, this process is very similar to scientific rigor, with experiments being designed with extensive time invested in observing and theorizing, unlike IT initiatives (Marchand and Peppard, 2013; Viaene and Bunder, 2011). Thus, several approaches may be tested against one another to determine the best method for the best solution (Liberatore and Luo, 2010; Viaene and Bunder, 2011).

Several processes for Analytics initiatives have been described, but they usually show remarkable similarities (Franks, 2014). After identifying and understanding the problem, specialists collect, prepare, and explore the data to eventually analyze it and create models to capture the patterns in it (Franks, 2014; Janssen et al., 2017; Leventhal, 2015; Provost and Fawcett, 2013). The results will be presented for evaluation, at least to the intended users (decision makers), and deployment into the business process concludes the process. Finally, the initiative shifts to feedback-based adjustments and maintenance to sustain the ongoing decision support activity (Larson and Chang, 2016).

The results – insight and knowledge – of an Analytics initiative are distinguished according to: (1) discoveries, which provide value in learning, or (2) Analytics products, which provide value in use (Larson and Chang, 2016; Viaene and Bunder, 2011). In deployment, these are distinguished by the use of a PowerPoint slide deck or code to deploy models or algorithms (Cady, 2017). In both forms, the results are provided to users in a processed way, which is intended to trigger decisions and actions (Bose, 2009; Davenport and Harris, 2007; Seddon et al., 2017). Consequently, either by taking decisions and actions directly from discovery, or by automated rules and decision-making/support, the users are benefitting from the effort to transform the Analytics results into consumable insights (Davenport and Harris, 2007; Ross et al., 2013). The tasks of Analytics initiatives are illustrated in Figure 21. Again, the numbers in superscript refer to the propositions explained below.

5.2.2.2 Process-accompanying conditions

Core to Analytics are data, which hold value and knowledge in form of insights. However, insights such as hidden relationships or uncovered patterns are costly to achieve (Bose, 2009; Marchand and Peppard, 2013; Watson, 2014). Moreover, insights must be deduced from the results of analytical methods by interpretation and sense-making (Seddon et al., 2017) and subsequently effortfully translated into actionable and understandable decision support for users (Barton and Court, 2012; Bose, 2009; Viaene and Bunder, 2011). This effort is reflected in literature by descriptions such as extraction, transformation, or unlocking (Acito and Khatri, 2014; Beer, 2018; Larson and Chang, 2016; Wixom et al., 2013). In addition, several data sources with big data characteristics might be integrated, increasing the effort (Bose, 2009; Chen et al., 2012; Kiron et al., 2012).

Concerning the specialists executing Analytics initiatives, the jack-of-all-trades Analyst idea is rejected for any larger and more complex initiatives (Carillo, 2017; Davenport, 2013; Davenport et al., 2001). Instead, these rely on cross-functional teams, a mix of technical and business knowledge, with individual team members contributing to insight generation through their knowledge and fostering learning by interacting with other team members (Larson and Chang, 2016; Marchand and Peppard, 2013; Seddon et al., 2017). While analytical and technical experts carry out the analytical work and ensure technical deployment requirements are met (Larson and Chang, 2016; Liberatore and Luo, 2010), cognitive experts contribute knowledge about how decisions are made and, as a result, how insights are delivered to the consumers of insights (Marchand and Peppard, 2013). Further, domain experts prioritize and direct opportunities and inquiries, identify challenges, validate results, and make sure deliverables meet business requirements (Larson and Chang, 2016; McAfee and Brynjolfsson, 2012; Wixom et al., 2013).

Organizations may also acquire expertise from the market by hiring experts or contracting to external organizations. Organizations that do so may lack experience in Analytics and want to evaluate opportunities (Bose, 2009). They may need a broad range of expertise and do not want to invest in building this full range, especially if a very specific expertise

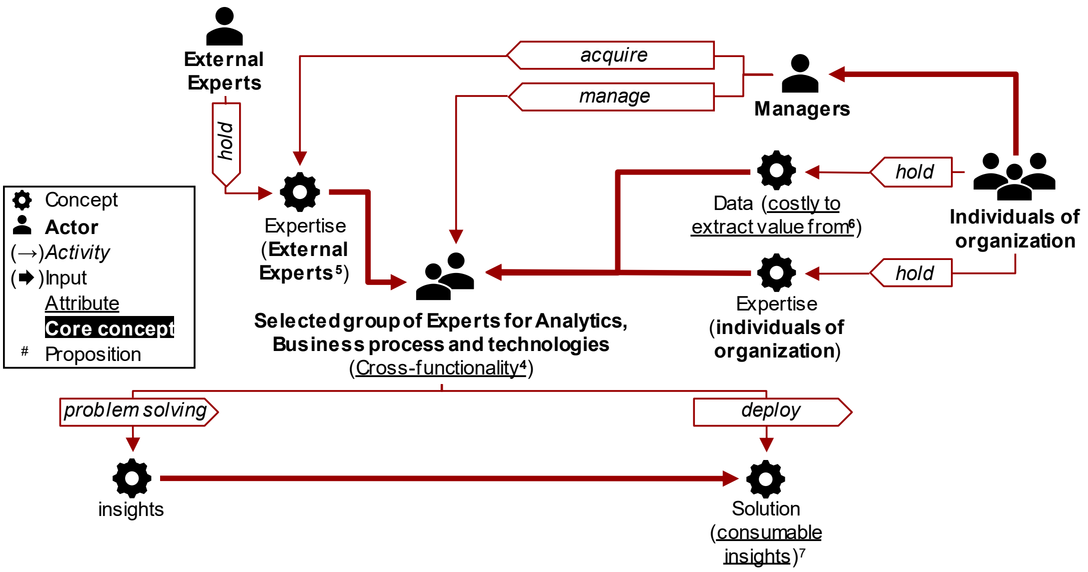

Figure 22: Process accompanying conditions illustrated

is needed (Carillo, 2017; Kiron et al., 2012). Further, the required expertise may be cutting edge and innovative, and therefore not broadly mastered, resulting in it only being accessible through the market (Barton and Court, 2012; Wixom et al., 2013). The process and its associated conditions are illustrated in Figure 22.

5.2.2.3 Advantages from Analytics and their requirements

By itself, the possession of Analytics capabilities or application of analytical methods has no inherent value (Gandomi and Haider, 2015; Holsapple et al., 2014; Larson and Chang, 2016; Seddon et al., 2017). The value is generated from using the capabilities and created insights, which requires them to be accessible or integrated into business processes to enable insight-driven decisions and actions (Bose, 2009; Kiron et al., 2012; Lavalle et al., 2011; Seddon et al., 2017). Hence, the advantages from an Analytics initiative are not provided by producing analytical results but from consuming them for decisions and actions (Ransbotham et al., 2015). This indicates the responsibility belongs to the users, as opposed to Analytics experts. Thus, the outcomes from executing Analytics initiatives are the users' process and behavior changes, and actions triggered by insight-driven decisions (Davenport et al., 2001). If decisions are made but not followed by actions, potential value is missed.

Gaining advantage from Analytics is further facilitated by a data-driven culture. This culture has been presented as strong moderator that positively influences the value generated by Analytics and the absence of which can negate the benefits from Analytics (Barton and Court, 2012; Ghasemaghaei et al., 2017; Ross et al., 2013). A data-driven culture is described as a common organization-wide culture that supports, promotes, and embeds shared analytics-driven ways of thinking, decision-making, and acting, and accepts data and information as critical for success (Barton and Court, 2012; Holsapple et al., 2014; Kiron et al., 2012). A data-driven culture supports a high degree of use of analytical tools to derive insights organization-wide, and demands decision-making and even challenging of prior beliefs based on the insight, which requires analytical skills and literacy (Barton and Court, 2012; Kiron et al., 2012; Marchand and Peppard, 2013). Insights are proposed to be generated and used at high frequency, such as by using insights in daily operations, making insights easy accessible on mobile devices, and continuously coaching staff to shift to data-driven decision-making (Barton and Court, 2012; Kiron et al., 2012; Ross et al., 2013; Wixom et al., 2013). To achieve the aspired-to degree and frequency, organizational structures are established in the form of strategies, policies, processes, and standards (especially for data) supporting the use of analytical tools, communication of analytical needs, and the use of the generated insight (Cao et al., 2015; Davenport et al., 2001; Ross et al., 2013).

The value gained from solutions resulting from Analytics initiatives is not durable. To ensure long-term value, Analytics solutions must be maintained and newly created. For maintenance, user feedback and business outcome have to be analyzed and evaluated to stabilize, adjust, and improve the solution (Larson and Chang, 2016; Lavalle et al., 2011; Liberatore and Luo, 2010). Further, the solutions can become outdated or misaligned, especially due to changes in data or the deployment environment, demanding realignment and adjustment to changes (Larson and Chang, 2016; Ross et al., 2013). Eventually, new forms of data can become available and can be integrated (Beer, 2018). In contrast,

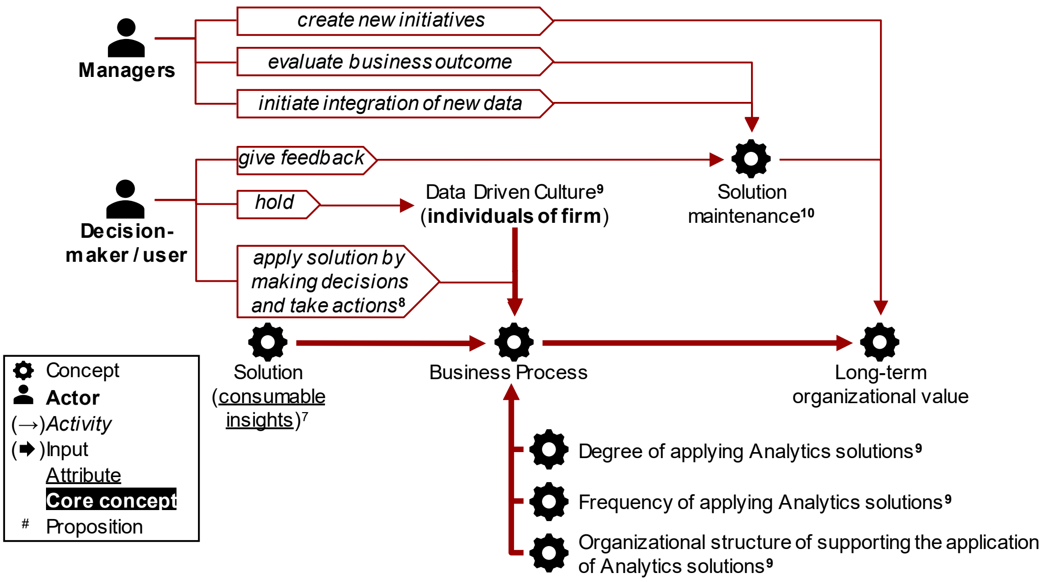

Figure 23: Enabling advantages from Analytics illustrated

creating new initiatives may include the introduction of completely new solutions or of already beneficial solutions to new organizational functions (Seddon et al., 2017). The former is necessary due to the limited lifespan of solutions in the absence of further adaptations or adjustments (Ghasemaghaei et al., 2017; Larson and Chang, 2016). The latter is necessary to broaden the range of functionalities supported by Analytics based on new needs and the intent to distribute the value from Analytics broadly across the organization (Beer, 2018; Davenport and Harris, 2007; Lavalle et al., 2011). These requirements to sustain the advantages from Analytics are illustrated in Figure 23.

Finally, direct attribution of value and benefits from Analytics is usually challenging (Larson and Chang, 2016). Direct effects are more effective, more informed, and faster decisions (Bose, 2009; Cao et al., 2015; Ghasemaghaei et al., 2017), which result in indirect effects, which are hard to attribute, such as improved decision outcomes, improved performance, production of knowledge, differentiation from competitors, individualization of goods and services, increased productivity, and increased profitability, while outperforming less analytics-driven competitors (Barton and Court, 2012; Bose, 2009; Holsapple et al., 2014; Kiron et al., 2012; Lavalle et al., 2011; Marchand and Peppard, 2013). The process of Analytics initiatives creating advantages for organizations is illustrated in Figure 24.

5.2.3 Parallelism of knowledge-based view and Analytics

The discussion above has presented KBV’s theoretical argumentation for competitive advantage generated from integrating and applying knowledge and the practical Analytics processes for generating advantages from analyzing data and applying the results. Both demonstrate immense similarity, assuming data to represent one of several portions of an organization’s knowledge. To answer the research question, Analytics is now examined for the rationale behind the practices. This rationale is compared for its resemblance to the argumentation of the KBV. In this research, confirming this resemblance is argued to provide support for an explanation of the competitive advantage generated from Analytics. If the empirical evidence does not show resemblance, either between the practices or the rationale for those practices, the explanation of generating competitive advantage from Analytics based on the KBV is not supported.

Consequently, components of the KBV have been selected and inquiries for empirical evidence have been made for practices in Analytics with respect to those components,

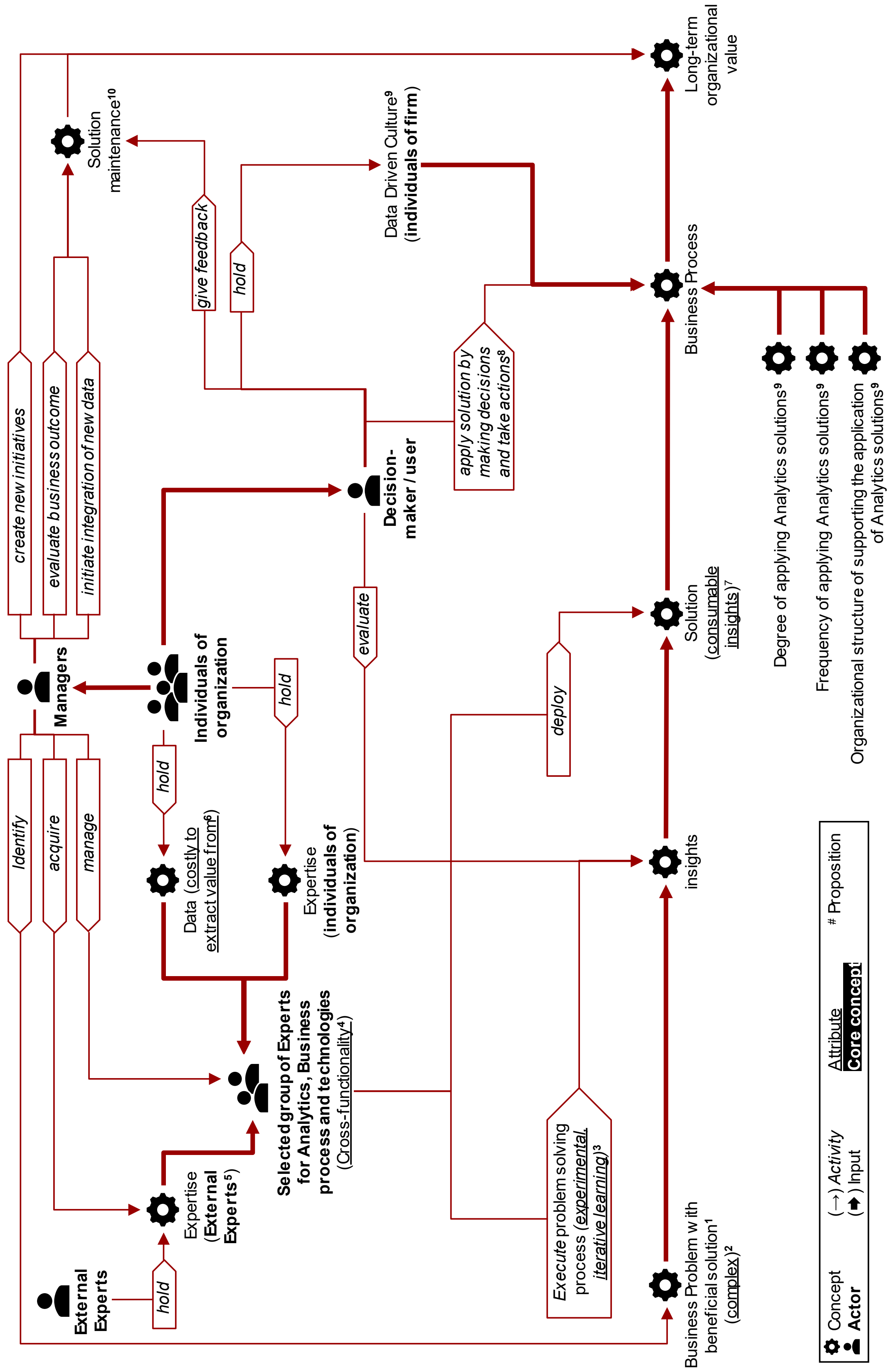

Figure 24: The value creation process of Analytics initiatives

including their rationale. The selected components represent key points of the argumentation for generating competitive advantage, which can provide proposed explanations – propositions – for practices in Analytics due to the resemblance between Analytics and the KBV. While the theoretical background presents practices in Analytics to provide evidence for their noticeable resemblance to the KBV and to formulate propositions, they will be treated as unknowns in the data collection. Data collection will also include collecting empirical evidence to explain different practices based on different intentions to disconfirm the KBV–Analytics resemblance, if in fact it does not exist.

The first selected component is the starting position, which consists of valuable problems to solve for knowledge creation in the KBV. These resemble the Analytics starting point of business problems to solve:

(1) **Proposition 1:** The most promising start for an Analytics initiative is supposed to be a problem (business question, business problem, opportunity to exploit, business target).

Second, the proposed foci of Analytics initiatives are complex issues with unprecedented requirements, which resemble potentially valuable ill-structured problems with high knowledge set interaction. Unprecedented expresses the characteristic of being unsolved for ill-structured problems:

(2) **Proposition 2:** Analytics initiatives intended to create highly valuable solutions are focused on complex issues with unprecedented requirements.

Third, the KBV suggests the heuristics solution search approach for ill-structured problems, resembling the scientific approach of iterative learning in Analytics:

(3) **Proposition 3:** The problem-solving process is an iterative learning process with experiments/tests of solutions giving direction for the next solution iteration.

The fourth component is the knowledge set diversity endorsed in the KBV, which expands the range of solutions, enabled by diverse individuals holding knowledge and taking different roles or specializations. It resembles the cross-functionality of teams contributing to data analysis:

(4) **Proposition 4:** Diverse roles in an initiative are relevant and covered by a selected cross-functional team with various different perspectives, expertise, and knowledge.

Fifth, even though it is a controversial aspect in the KBV, inclusion of market actors is selected. Including them for problems with fewer needs of knowledge sharing and access to new knowledge sets resembles acquiring external expertise from the market already available as specialized expertise or gaining access to innovative expertise in Analytics:

(5) **Proposition 5:** External Expertise is necessary to exploit market-available specialized expertise or gain access to innovative technologies or methods.

The sixth component selected represents the assumption, as stated above, that data present a portion of organizations' knowledge. The KBV argues that it is necessary to exploit tacit knowledge since tacit knowledge fulfills the characteristics of a resource necessary for competitive advantage, but which is costly to integrate. This resembles the costliness of extracting insights from data:

(6) **Proposition 6:** Creating valuable insights and Analytics solutions based on data is costly, with several barriers to overcome.

Seventh, to make use of tacit knowledge, the KBV explains the need for integration mechanisms, which are proposed to integrate knowledge into the value creation process suitable to the task, process, and organization. This resembles the creation of consumable insights for users in the form of discoveries and Analytics products in Analytics:

(7) **Proposition 7:** For deployment, the user is provided with consumable insight (one-time insight or an Analytics product) enabling him to work directly with the insight.

The previous component is the prerequisite to allow the eighth component needed for competitive advantage explained in the KBV, the necessity of applying the integrated knowledge in value creation. Resemblance can be found in the user's responsibility to adjust the process and make decisions and take actions from insights explained in the Analytics literature:

(8) **Proposition 8:** After deployment, the user's responsibility is to integrate insight into processes, make decisions, and take actions to create the aspired-to value.

The ninth selected component comprises the moderators for the competitive advantage from the application, which are the common knowledge and the characteristics of its contribution to the knowledge integrated to facilitate competitive advantage. These resemble the data-driven culture on which advantages from Analytics depend:

(9) **Proposition 9:** To enhance the value from Analytics, a data-driven culture has to be built, which is facilitated in Analytics' broad and frequent use, and supporting organizational structures.

Tenth and finally, to make the competitive advantage sustainable, the organizational capabilities from knowledge integration, including knowledge concerning existing capabilities, need constant renewal, which resembles the maintenance of Analytics solutions and their renewed creation to ensure long-term advantages from Analytics:

(10) **Proposition 10:** To maintain value generated by insights and solutions in the long-term, maintenance processes based on added data, evaluation of business outcomes, and user feedback are necessary.

The proposed resemblance has two implications. First, if a process to exploit organizational resources exists that leads to advantages and benefits, is employed by organizations, and markedly resembles the knowledge-based view, it would contribute to the validation of the knowledge-based view. Second, if this remarkable resemblance is confirmed and as a result the Analytics process fits the KBV, the advantage from the process would be competitive advantage.

5.3 Methodology

This research aspires to explain how competitive advantage is generated from Analytics. The foundation for that explanation was laid in the theoretical background and the resulting propositions are subsequently tested using empirical evidence. For “How?” questions, the methodology of case studies is appropriate (Yin, 2014). Case study research has been used to confirm the link between scientific theories and phenomena by scholars in information technology and strategic management. For example, business practices and investments have been linked to the resource-based view and the extended resource-based view to argue for competitive advantage as a benefit of these models (Lewis et al., 2010). A combination of contingency theory, dynamic capabilities theory, and task/technology-fit was used to provide a theoretical basis for the field of Business Process Management (Trkman, 2010), and the resource-based view and the related concept of resource orchestration has been used to explore how manufacturers adopt e-commerce (Cui and Pan, 2015). Seuring (2008) has underlined the benefits and demand for empirically based case study research to enhance understanding of supply chain management.

5.3.1 Research Design

Case study research can be deployed in a way that is exploratory and/or explanatory (Yin, 2014), and this study aspires to the latter. Hence, prior to data collection, literature was studied to develop a conceptional framework and testable propositions (Miles et al., 2014; Voss et al., 2002; Yin, 2014). The conceptional frameworks are presented in Figure 20 and Figure 24. The propositions are presented in Section 5.2.3. The first framework comprises key components of the KBV, which provide a theoretical explanation for sustainable competitive advantage generated from knowledge. The second framework comprises recommended practices for Analytics initiatives that the literature has established as relevant for generating benefits and value, but with limited rationale for their relevance. Using the first framework as reference, case study research is employed to provide empirical evidence to confirm the sustainable competitive advantage generated by Analytics by explaining causal relationships thoroughly. This design fits the case study research objective of providing a causal diagnostic pursued with a pathway strategy that is expected to identify the mechanisms explaining the relationship under investigation and show its plausibility (Gerring and Cojocaru, 2016).

For the causal diagnostic pathway strategy, a multiple-case study approach is recommended, preferably with stable background factors (Gerring and Cojocaru, 2016). This stable background is implemented by constraining the study to the field of LSCM. This field is exceedingly familiar to the scholars conducting the research. Due to several globally dispersed actors in the varying flows of materials, information, and funds, this field experiences a high level of complexity and process heterogeneity (Bowersox et al., 2007; Simchi-Levi et al., 2003; Wang et al., 2014), which entails potentially interesting cases for Analytics solutions employed for controlling the flows. In accordance, LSCM is considered as an early adopter of Analytics (Davenport, 2009) and is considered as a data rich field with promising returns from Analytics (Jeske et al., 2013; Kiron et al., 2012). Despite these circumstances, many organizations in LSCM show reluctance towards Analytics adoption (Brinch et al., 2018; Kersten et al., 2017; Thieullent et al., 2016), although this audience might develop greater interest based on research insights into Analytics associated with their own field, and may eventually be persuaded regarding the value and benefits.

Selecting cases from any field regarding Analytics initiatives brings foreseeable issues of limited availability and willingness of experts to respond to research inquiries. Relevant and identifiable experts for data collection are rare and in high demand. Further, with Analytics expected to create advantages over the competition, it cannot be expected that extensive internal documentation will be provided. In summary, it is foreseeable that limited depth can be achieved per case. However, critical analysis of case study research has demonstrated acceptance for limited depth in multi-case research, since multiple cases supporting the results increase the confidence and robustness of results, and provide more sophisticated descriptions and more powerful explanations (Miles et al., 2014; Voss et al., 2002; Yin, 2014). As a result, a multiple case study was seen as appropriate to counter accessibility issues while adhering to constraints of time and resources. Further, to increase accessibility, the cultural and language distance to this study was kept short by limiting the sample to organizations operating in Germany. A final number of eight cases was achieved. These cases were theoretically sampled such that they were chosen explicitly – not randomly – to achieve greater insights (Eisenhardt, 1989).

5.3.2 Data Collection

Following established instructions (Voss et al., 2002; Yin, 2014), a case protocol was created, including research design, case selection criteria, relevant sources of evidence, and interview questions. The protocol was reviewed by two scholars and adapted accordingly. The sources of evidence to be collected included semi-structured interviews, relevant presentations by interviewees and case organizations, relevant publicly available documents from case organizations on LinkedIn, Xing, organizations' websites, as well as blog entries, videos, and white papers, in addition to third party reports and articles about the case organizations on relevant topics. These sources of evidence were chosen for triangulation (Yin, 2014). The questions were designed to openly ask about aspects of Analytics initiatives, with implied unknowingness, to encourage interviewees to provide detailed explanations and reasoning (Yin, 2014). Further, inspired by descriptions on rival explanations/alternative theories (Voss et al., 2002; Yin, 2014), rival explanations about the generation of value from Analytics were developed prior to the data collection and reviewed by scholars, showing a high degree of disjunction among the propositions. The data collection was expanded to include these rival theories. Thus, after answering the open questions about the process aspects in the semi-structured interviews, the interviewees were asked about other explanations (rivals or propositions, depending on the open answer) to obtain their comments on all explanations. Typically, interviewees

No.	Aspect	Proposed explanation ("Proposition")	Rival explanation 1	Rival explanation 2	Rival explanation 3
1	Staring Position	The most promising start for an Analytics Initiative is supposed to be a **Problem** (Business Question, Business Problem, Opportunity to exploit, Business target)	The most promising start is the exploration of specific **Data (sets or sources)**, which are supposed to be exploited	The most promising start are **competitors' solutions** observed in use	The most promising start is the expressed **desire to do something with data** in the organization
2	Focus of an Initiative	Analytics initiatives intended to create highly valuable solutions are focused on **complex issues** with unprecedented requirements	Analytics initiatives intended to create highly valuable solutions are focused on **simple issues**, such that known solutions can be economized	Analytics initiatives intended to create highly valuable solutions are focused on improving solutions of **issues previously addressed** with other means (brownfield)	Analytics initiatives intended to create highly valuable solutions are focused on replacing creative and ideation methods to economize invention **design issues**
3	Problem solving Process	The problem-solving process is an **iterative learning process** with experiments / tests of solutions giving direction for the next solution iteration	The problem-solving process is in an unstructured **trial-and-error manner** with testing different solution path until one satisfies (little learning from trials)	The problem-solving process is a **straightforward** execution of clearly defined and plannable tasks and work packages that are rarely adapted.	The problem-solving process is intended to apply data analytical methods to **provide evidence for the customers intuition** (no exploration or learning)
4	Roles in an Initiative	Diverse roles in an Initiative are relevant and covered by a **selected cross-functional team** with various different perspective, expertise and knowledge	The single relevant role is a **jack-of-all-trades Data Scientist**, who executes the whole Analytics Initiative and covers the full variety of tasks	IT covers the relevant roll of data provider making data available and the users covers the Analyst role and **users build own solutions**. No Data Scientists are involved.	With little fix roles and in a democratic way, anyone can express their opinion on solutions to be developed in a **non-selected cross-functional** team and execute tasks.
5	External Expertise	External Expertise is necessary to **exploit market available specialized expertise or gain access to innovative technologies or methods**	External Expertise is necessary for all Analytics initiatives and it is best for companies to **concentrate on the core business**	External Expertise should not be sourced for Analytics initiatives and should **completely developed and sourced inhouse**	External Expertise is necessary for the **strategically important Analytics initiatives** that are supposed to deliver a competitive edge in the market
6	Data	Creating valuable Insights and Analytics **solutions based on data is costly** with several barriers to overcome	Creating valuable Insights and Analytics **solutions based on data is simple** with easy to overcome barriers	Creating valuable Insights and Analytics solution based on data will result in outcomes that **don't exceed those based on human intuition**	Creating valuable Insights and Analytics solution based on data **depends on having large volumes** of data available and collection capabilities
7	Deployment	As deployment, the **user is provided with consumable insight** (one-time insight or an Analytics product) enabling him to directly work with the insight	As deployment, the **user's process will be taken over by a data scientist** subsequently executing the process based on created insights due to their complexity	**As deployment, any user is completely removed** from the process, since Analytics aims to completely automate processes	As deployment, users are provided with access to data or results from analytical methods, while **generating insights for processes are in the user's responsibility**
8	User Responsibility	After deployment, the user's responsibility is to **integrate insight into processes, make decisions and take actions** to create the aspired value	After deployment, the user's responsibility is to **evaluate whether to use the insight or rely on his intuition** to create the aspired value	After deployment, the user's responsibility is to **invest time to understand and reconstruct** the generation of insights to be convinced of trustworthiness to create the aspired value	After deployment, the user's responsibility is to continue own tasks, while **transparency of mistakes and concern for accountability stimulates user** to better performance
9	Organizational Factors	To enhance the value from Analytics a **data-driven culture** has to be build, which is facilitated in Analytics' broad and frequent use, and supporting organizational structures	To enhance the value from Analytics, all employees need extensive knowledge in Analytics such that **all employees are data scientists** or equivalently educated	To enhance the value from Analytics, **organizational culture is not influential** since Analytics is a tool and by using the tool right	To enhance the value from Analytics, an **intuition-based culture** has to be built, which is facilitated in critical and skeptical views to maximize solution validity before deployment
10	Long-term usability	To maintain value generated by insights and solution long-term, **maintenance processes based on added data, evaluation of business outcome and user feedback** are necessary	To maintain value generated by insights and solution long-term, no actions are needed because deployed solutions are **stable and provide generally valid** insights and value	To maintain value generated by insights and solution long-term, **insights and solutions need to be adopted to new users** to make them productive with the solution	To maintain value generated by insights and solution long-term, insights and solutions need to be replaced when **new technologies** become available

Table 1: Propositions and rival explanations

argued strongly against the rival explanations, enriching the evidence for the propositions but also revealing the incompleteness of the propositions, thus confirming the value of this research design.

The case protocol was revised during data collection to add as much depth as possible by eliminating weaknesses and blind spots (Eisenhardt, 1989; Yin, 2014), conducting pilot cases for each category, and subsequently reviewing and revising questions and rival explanations. The propositions and their final rivals are presented in Table 1. Pilot studies were conducted for the following categories: (1) manufacturers using Analytics for LSCM processes or Logistics Service Providers using Analytics ("LSCM organizations"), and (2) Analytics Service Providers with distinct experience working with and providing services for LSCM. Multiple inquiries to target retail organization did not produce a pilot case, leading to the exclusion of this category.

ID	Position	Organization sector	Organization size	Experience in Analytics [yrs]
A	Head of Analytics	Software	Small	11-15
B	Director Analytics	Software	Large	11-15
C	Sen. Manager Analytics	Chemicals	Large	1-5
D	Sen. Manager Analytics	Software	Large	6-10
E	Head of Analytics	Logistics	Large	1-5
F	Sen. Data Scientist	Commercial vehicles	Large	6-10
G	Sen. Manager Analytics	Pharmaceutics	Large	1-5
H	Sen. Manager Analytics	Software	Large	16-20

Table 2: Case study interviewees and organizations

For the interviews, a short protocol was created and sent to previously contacted experts to evaluate their eligibility for the study and as preparation. The evaluation led to the exclusion of interested but ineligible experts. During the pilot cases, neither snowballing via the interviewees nor direct contacts produced further interviewees. For reasons of consistency, for additional cases also only one participant in a key position was interviewed per case organization. In summary, eight interviews were conducted via phone and web conference software with a duration of 58.5 minutes on average. The interviewees and their organizations are listed in Table 2. Further, a total of 235 documents were reviewed. All sources of evidence were organized in a case database (Yin, 2014).

5.3.3 Data Analysis

For data analysis, each case is considered as single experiment that is replicated to strengthen confidence in the propositions or provide disconfirming results to shape the theory (Eisenhardt, 1989). This was applied to all explanations, propositions, and rival propositions. Thus, as opposed to Grounded Theory (Strauss and Corbin, 1998), the investigation did not synthesize the results from multiple cases, but every case was investigated individually for conformance to the explanations by comparing the evidence to the explanations (Miles et al., 2014; Voss et al., 2002; Yin, 2014). Disregarding the rare occasions of no evidence collected for an explanation, which occurred for few rival explanations, the conformance of single explanations over all cases was determined by considering the individual results of each case for a single explanation together.

In detail, interviews and documents were analyzed using hypothesis coding (Miles et al., 2014) based on propositions and rivals, since a comparison of theoretical explanations (or predictions) to the collected evidence is recommended (Rosenbaum, 2002; Yin, 2014). Further, for within-case analysis, the coded evidence for specific explanations was analyzed for each individual case and a synthetized description collected in a matrix case display (Eisenhardt, 1989; Miles et al., 2014; Voss et al., 2002). After concluding the within-case analysis for all cases, cross-case analysis was performed explanation by explanation (Eisenhardt, 1989; Voss et al., 2002). Cross-case analysis took place in two steps. First, explanations (propositions and rivals) of each case category (LSCM organizations and providers) were compared within the categories and a description coherent for the categories for each explanation was developed. Second, the descriptions of the categories were compared to determine differences between the groups and to develop a coherent description for each explanation, valid according to the collected evidence.

5.3.4 Trustworthiness

For trustworthiness, the quality criteria of Yin (2014) were considered. For reliability, a case study protocol was developed and discussed with scholars. Further, a case study database was established ordering collected data by case, systemizing individual documents in the associated cases, and recording metadata. Internal validity was ensured during preparation of the research design by documenting and displaying explanation building for the proposition (Section 2). During data collection and analysis, internal validity was ensured by explicitly designing rival explanations, which were discussed with scholars, included in data collection, and compared to the propositions in the data analysis (Section 4). For external validity, literal replication logic was strengthened by selecting eight case organizations executing Analytics initiatives in LSCM. Construct validity was addressed by using multiple sources of evidence including interviews and a variety of documents, as well as by providing the results of this research to the interviewees with a request for comments.

5.4 Results and Discussion

This section presents and discusses the results of the case studies regarding support, rejection, and supplementation of propositions. Eight out of ten propositions were supported with consistent results from the case studies, but were supplemented by adjustments and exceptions. The advantage of the research design is to understand how these adjustments and exceptions help to shape the theory that formed the initial propositions. Rival explanations contributed to improved understanding.

In the following, "user" describes the employee in a business process intended to use the results of an Analytics initiative continuously in the form of an Analytics product or an accessible static discovery. "User" further describes an eventual customer of an organization using the results, or an employee whose individual task is automated.

5.4.1 Starting position for Analytics initiatives

According to the evidence, the most promising starting position of an Analytics initiative is a business problem or business question – preferably defined by business users. Interviewees were confident in identifying problems by talking to users in business processes and, if a problem was not formulated by the users, interviewees stressed to identify users and get them involved. Such a business problem allows specification of the proposed solutions. In this way, it becomes more likely that the initiative will develop solutions that users are willing to use, that fit to users' and business processes' needs and requirements, and that typically show better performance. These solutions become more likely to be operationalized and realize their expected value. Their benefits become tangible, and the solutions' impact and value assessible. Hence, initiatives can be prioritized and, since benefits are easier to communicate and explain, create buy-in from sponsors in the form of resources, funding, personnel, and power to overcome barriers. Activities increase in solution-orientation and enhance the process (e.g., reduced planning effort; clearer selection of solution-progressing tasks and increased focus of tasks; easier identification of needed resources, data and relevant stakeholders; less delays, determinability of sufficient solution performance levels and test criteria; increased agreement between and more solution-oriented ideas from team members). In conclusion, this approach directs Analytics efforts to create value effectively and efficiently, by considering the value of solutions and costs of developing solutions, while enhancing value realization and reducing overall costs. This resembles the approach of solving valuable problems within the KBV and supports Proposition 1.

However, Proposition 1 is supported with modifications. First, data must be catalogued and inventoried to understand availability, conditions, and developable solutions. Second, Analytics must be the most promising way to address the problem as compared to other techniques.

Rival Explanation 1 to Proposition 1 – starting from data – was rejected. This approach was suggested in some cases as a starting position that is sometimes taken or considered as an option, but was explained to take longer, be likely to result in unusable or irrelevant solutions, and not to motivate sponsors. However, data exploration was declared to be an essential step after problems are understood to create understanding about the data (formats; granularity; timeliness; quality; ability to integrate; what data describes; what data is, is not, and should be collected). Moreover, exploration for taking inventory and cataloguing data and data sources is necessary before Analytics initiatives are executed to enable the selection of the most promising Analytics initiatives. This is important, since these first initiatives can either build momentum or "burn" the topic, and deficits in the condition of the data foundation soon become apparent. Overcoming these deficits is a time and resource consuming endeavor, which neither provides gleaming benefits nor convinces sponsors, but it is an important enabler for executing initiatives.

Starting from a solution seen at competitors, Rival Explanation 2, was rejected as starting point for a competitive advantage. Copying competitors' solutions can be a good start for non-critical solutions. This approach can further be inspiring for organizations reluctant with Analytics. This corresponds to findings indicating an increase of adoption of Analytics if competitors are using it (Lai et al., 2018). However, such solutions are unlikely to have similar impact at the focal organization. The context dependency and need for adaptation of Analytics solutions is very high. Further, this approach does not put organizations in a position of competitive leadership. For a competitive edge, the observed solution must be made better – an endeavor which is resultingly a business problem.

As it is does not indicate any clear path of action, the desire of doing something with data as advertised in conferences or promoted in press releases, which is the third rival explanation for the most promising start, was also rejected. Any Analytics initiative starting with such a lack of focus leads to discussions about what to do, likely delays any solution, and likely creates no valuable solution. However, outside of Analytics initiatives, this desire, formulated and communicated by top management, can push investment decisions, get users to think about business problems that could be addressed with Analytics, and create visibility for Analytics in organizations. Investments are needed for technology, analytical tools, and for developing data collection, storage, structure, quality, and standards. Getting users thinking about long unsolved problems and having their curiosity stimulated is a substantial driver for tackling problems with Analytics. Further, the visibility disseminates benefits and ensures interest in Analytics is sustained.

Regarding LSCM, the case organizations have exploited the proposed starting position to promote the use of Analytics. LSCM users have various problems of transparency and visibility at hand, for example, regarding processes, markets, and competitors. Solutions to these problems provide them with tangible value, including identification of weaknesses, improved planning, reduced cost, faster response times, and reduced firefighting. Addressing these problems created a more supportive approach to introducing Analytics to LSCM.

In summary, Proposition 1 is supported and all rival explanations to it are rejected.

5.4.2 Focus of Analytics initiatives

To gain valuable solutions from Analytics typically means addressing business problems that are complex because either a lack of appropriate means omitted to solve them so far, or because previously addressed problems remain business critical and enhanced solution performance is desired. Characteristics of complexity are numerous, including time criticality of solutions reaction, need for a high level of transparency across organizations or supply chains, or the amount of data and information to be combined (often exceeding human cognitive capacity). Concerning this amount of data, complexity further results from internal or included external factors, actors, object behaviors, and contextual specifics (rules, local characteristics, constraints), which can be interrelated or interacting. Controlling this diversity of input, processed with novel requirements on speed and accuracy, is a salient ability of Analytics and allows organizations to approach completely new problems. The resulting faster decisions and improved decision outputs provide high returns and savings. Further, through maturing in Analytics by executing initiatives, organizations build abilities to address more complex problems. This focus on complex problems for high value and the maturing from solutions resembles the focus on complex ill-structured problems displayed in the KBV. This supports Proposition 2.

Nonetheless, relatively simple problems with high returns – quick wins – represent exceptions to Proposition 2. Further, the use of Analytics must be reasonable for the problems and should not be excessive, demanding solutions via other means if more appropriate. It was emphasized that initiatives need to be net beneficial.

Rival 1 for Proposition 2, which opposes Proposition 2, was rejected since simple problems, as a focus of Analytics, usually do not provide high returns. In exceptional cases, simple problems may result in valuable insights, and solving complex problems may not provide valuable insights. In this regard, interviewees referred to simple in relative terms, associated with more established methods and tasks, but which still require well-trained experts. Nevertheless, this focus is beneficial in early organizational maturity with Analytics, during which complex problems induce a higher probability of failure and could give Analytics a bad reputation in an organization. Simple problems, in the sense of controllable problems, were described as the foci of initiatives intended to automate decision-making with well understood decision options and whose impact could be comprehensively identified and approved. It was repeatedly explained that even small positive returns are still positive returns, suggesting a cost-benefit perspective as an important paradigm for Analytics.

Rival Explanation 2, of solving previously addressed problems as a focus of Analytics initiatives, was supported as a supplement to Proposition 2. Considering the aspired-to enhanced level of performance for identifying solutions to business problems through the presentation of an ill-structured problem with unrevealed and unmastered knowledge set interactions, this rival explanation resembles the KBV. Implemented solutions to business problems are usually justified by their business criticality. If this criticality remains with a need for enhanced solution performance and Analytics is likely to deliver it, an Analytics initiative consequentially creates high value comparable to completely new problems, as specified in Proposition 2. This value can result from higher performance, higher efficiency, more relevant insights, standardization of solutions for increased usability and accessibility (e.g., standardizing spreadsheet solutions), or new approaches (e.g., from reactive to proactive). Such initiatives support maturing in Analytics, since many aspects of the problem are well understood, benefitting the solution development. Again, it was argued that benefits exceeding the costs and proper priority are deciding factors for executing initiatives.

The third rival explanation was rejected, since Analytics is not focused on replacing ideation and creative methods. It is rather a supportive input to ideation and guides innovations into the right direction to exploit opportunities. In contrast, creativity is vital to identify the right business problems to address. Analytics can support the development or even be part of new value-added features, services, products, contract formats, and business models, while creativity and ideas are needed to design their monetization. However, the case studies presented a tendency to address internal process improvements with higher priority compared to building customer facing solutions.

According to Proposition 2, the complex issues currently the focus of Analytics initiatives in LSCM are manifold. LSCM organizations want to understand customers (what they do and need), assess process quality in real-time, and predict critical conditions of systems and assets such that countermeasures are resource and cost efficient. Asset fleet utilization is expected to be increased beyond non-Analytics limits and needs to gain capabilities for same day and same hour delivery under pressure on margins. Finally, more individualized services are anticipated to be provided due to Analytics, which is a paradigm shift from economies of scale and scope.

In summary, Proposition 2 is supported with acknowledge exceptions and Rival 2 is supported, which supplements the proposition. Rivals 2 and 3 are rejected.

5.4.3 Problem-solving process

Case studies presented the problem-solving process of Analytics initiatives to be iterative, with future iterations being guided by and extensively dependent on learnings from previous iterations. Further, the solutions of iterations are not put into trial in processes to see whether they fail or not. They are rather considered as intermediate states (proof-of-concept, pilot, prototype), which are the basis for discussions between solution developers and users, joint interpretation of results, validation of results, and making use of users' knowledge to guide the problem-solving process. According to interviewees, such iterations simplify the integration of several perspectives. Iterations are further supported by establishing the objective of initiatives at an early point to reduce ambiguity (e.g., memorandum of understanding, letter of content), and by agile sprints, as recommended by Larson (2016), in which tasks are focused on the next agreed intermediate state. As a result, this approach ensures knowledge transfer in iterations, in the form of user feedback, to ensure the selection of the relevant knowledge of the users (addressing intermediate solutions' deficiencies and gaps to expectations, domain knowledge guides solutions' improvement) as well as from the solution developers (methods to implement users' feedback). Thus, intermediate states are used for anticipated necessary interaction between users and developers. This resembles the heuristic solution search presented in the KBV and supports Proposition 3, although constrained by certain adjustments.

Adjustments emerge from the rival explanations. First, while the problem-solving process is iterative, initiatives follow a certain, structured approach, such as the repeatedly mentioned CRISP-DM model. One interviewee explained: "These projects are deeply unstructured, but you can approach them very structured". Second, Analytics products are also deployed with the intent to advance the solution based on user feedback, which at first glance resembles trial-and-error. However, this requires a quite advanced solution that is improved from feedback instead of radically changed.

Rival Explanation 1 to Proposition 3 was rejected because creating a valuable Analytics solution that users like to use requires continuous feedback during solution development. A trial-and-error style approach based only on past experience with positive and negative outcomes in developing solutions, neglecting necessary user and context adjustments and attempting to deploy without prior user feedback, is likely to produce inappropriate solutions that are not accepted by users.

As explained above, problem-solving is not straightforward, and Rival 2 is rejected. But structures for initiatives exist that guide users through various well-developed phases (e.g., CRISP-DM phases) that enfold the problem-solving iterations. Iterations and agile sprints do not facilitate chaos or lack of control. They need rules, structures, and documentation requirements such that the organization can repeat, recreate, and learn from initiatives. In this regard, it has been emphasized in the case studies that Analytics is not "just algorithms", it is the whole process around the algorithm that intends to generate value for organizations. Still, the process may be disrupted by stakeholders changing opinions, unclear decision structures nullifying previous decisions, or unanticipated data and technology issues setting the initiative back. Increasing maturity with problems, technologies, and Analytics reduces these disruptions.

While the problem-solving is guided by users' knowledge and intuition – a distinction that will be discussed below – it is not intended to use Analytics to confirm users' intuition or expectations to "play politics". Thus, Rival Explanation 3 is rejected. If the intuition were correct, the generated benefit is more certainty in actions providing limited value. If it is wrong, results that provide some confirmation could be fabricated, but this does not provide value, would not lead to actions in the best interest of the organization, and would be malpractice. However, interviewees also explained they had not observed this behavior. The strength of Analytics is seen in overturning existing business thinking and practices if a better outcome can be achieved differently.

It was emphasized that the iterative approach is specifically needed in LSCM to understand the perspective on a problem. Regarding forecasting of demand and capacity or the assessment of quality and performance, there are various perspectives in LSCM that require different aggregation of timescales, entities, and processes for the seemingly same problem. Iterations are essential to filter the correct perspective and informational needs.

In summary, Proposition 3 is supported, with all rivals being rejected.

5.4.4 Roles in Analytics initiatives

The evidence shows that Analytics initiatives are based on constantly interacting cross-functional teams with members filling different roles to perform different tasks. In particular, the inclusion of users, permanently or accessible at short notice, was highlighted. Users' inclusion enables solutions' dedication to users' needs, their operationalization, and their impact on business processes, since users have deep knowledge about the process (understand data and contextual meaning, understand required solution performance, know local specifics of decision-making, special business rules, and requirements, and factors impacting the outcome). They help to identify difficult to reach data sources, as one interviewee explained: "Excel spreadsheets are very popular, again and again". Apart from users, diversity of team members provides diverse skills and specialized knowledge, and diverse talents, perspectives, experience, and interests (a vital motivational factor). This mix enables more, better, and unconventional innovative ideas in Analytics initiatives, provides synergies, and accelerates the problem-solving process. Tasks can be distributed across the team to gain efficiency from specialization and manage the high workload. This resembles the KBV's argument for a group of specialized individuals required for knowledge creation from combining diverse knowledge sets and supports Proposition 4. Members were also explained to speak different "languages" due to their different cognitive concepts requiring a "translator" who has enough knowledge about the different roles to understand and connect the team members, comparable to the argument in the KBV. This role was explained to be even rarer than great data scientists.

Again, an exception applies to Proposition 4, since different roles may be filled by the same team member depending on the size and complexity of the initiative. Not all Analytics initiatives are intended to place an organization ahead of the competition, change the business model, or master the most complex business problems. Thus, unconventional and innovative ideas, synergies, or management of high workloads are not required for all initiatives.

However, uniting several roles has a limit and as a result the jack-of-all-trades data scientist specified in Rival 1 was rejected. Interviewees explained that their organizations' data scientists usually have a strong mathematical background (mathematics, physics, statistics), often with a PhD, since their tasks and core expertise are to make the most of data (analyzing, modeling, creating algorithms). They agreed that it is easier to learn new data tools with this background than the other way around. However, jack-of-all-trades data scientists were sought to find, but in the rare instances of finding one, they were extensively more expensive than a diverse team, thus eradicating their benefits. Data scientists are generally expensive and should focus on the data analytical tasks they are best trained for, as a matter of resource efficiency. They might do small initiatives on their own, but other initiatives would be physically challenging due to the workload – "It doesn't scale". This data scientist would rather be a single source of failure and interrupt the entire initiative in case of illness. Moreover, an idea of omnipotent data scientists contradicts the value of business experts and users, who have effortfully acquired knowledge and experience handling complex tasks. This idea disrespects them and their contribution, which can result in losing their eventually needed collaboration.

Rival Explanation 2 of users executing the initiatives was rejected since users usually lack knowledge and experience needed for Analytics initiatives or are occupied with their business processes, on which they are expected to work. Further, data literacy and knowledge on technologies may also be missing, and training would be extensive and require their affinity for the topic. With so called "self-serving analytics", users are increasingly getting involved with analytical tools, but these are often specifically developed or adjusted for users' empowerment (e.g., supporting workflow, providing relevant options as selectable) and require prior Analytics initiatives for their development. Thus, established methods are democratized instead of users working on leading edge problems. However, this reduces the workload of data scientists, who can then work on complex problems and accelerate gaining value from those.

Case studies indicated that the involvement of employees only weakly related to the business problem can be helpful in certain situations that require creativity and additional perspectives. Marchand and Peppard (2013) recommended such action as a strategy to introduce new ways to solve problems and overcome myopic views on data initiatives. However, this could also lead to revisiting already dismissed ideas and more discussions. Any strong voice intentionally or unintentionally putting their own needs first could divert the configuration of the intended solution away from users' needs. Further, input not relevant to the solution can disrupt and delay progress, which creates inertia in initiatives. Thus, Rival Explanation 3 was rejected.

In LSCM, putting the proposed cross-functional teams into practice comes naturally. LSCM as business function or business model usually interacts with many cross-functional actors and must fulfill the role of integrator. In LSCM organizations with an end-to-end vision of their supply chain, this is scaled to cross-organizational teamwork. Thus, working in cross-functional teams is the status quo for LSCM and nothing new due to Analytics.

Summarizing the above, Proposition 4 is supported, and all rivals have been rejected.

5.4.5 Including external expertise

Externals such as providers with high Analytics maturity are included in Analytics initiatives to develop better and cheaper solutions, because they are familiar with the problem and their expertise is an efficiently purchasable commodity. Including externals was further reported as beneficial for gaining access to specialized, innovative, and niche analytical methods and technologies. In accordance with Proposition 5, they are included when organizations have no interest in building expertise in rarely needed methods and technologies. However, organizations also include externals to build expertise and develop self-sufficiency, which goes beyond the proposition. Evidence clearly displays the adoption of Analytics as an effortful maturation, whether initially or for adopting Analytics innovations in mature organizations. This maturation is accelerated and reduced in stress and cost by appropriately knowledgeable externals with the intention of supporting maturation by executing co-creative Analytics initiatives. During maturation, externals can generate "buy-in" from sponsors by showcasing completed initiatives and value from Analytics and their experience reduces the risk of failure and "burning" the topic inhouse. However, the goal must be to develop internal expertise and self-sufficiency, since this is vital for the organization to develop inherent ideas for initiatives and trust from users. Thus, these co-creations are successful if externals eliminate the need for their expertise (not necessarily for their technologies), while this success provides a basis for new collaborations on different or more advanced topics. This partly resembles the inclusion of market actors for problems with fewer requirements and access to more diverse knowledge as explained in the KBV, but Proposition 5 must be rejected since it does not represent the full situation and misses an essential part of the inclusion of externals into Analytics initiatives.

More diverse but regular modes of cooperating with externals were reported, also not covered by Proposition 5. These include using externals as an “extended workbench” to gain flexibility, or for critical and urgent problems, regardless of the Analytics maturity of the organization. Further, externals may have access that cannot be substituted in other ways, such as solution providers that include data from other customers into a solution to enhance it. A minority of organizations always include externals to gain more diverse perspectives. Also less regular and outside the narrow focus of using externals for knowledge sourcing is the sharing of knowledge and resources to develop a collaborative solution for the market in a strategic partnership.

Rival Explanation 1 of companies focusing on their core competencies and leaving Analytics initiatives to externals was rejected in consideration of competitive advantage. While uncritical business problems with mature solutions exist, saving time and costs, building organizational self-sufficiency in Analytics was emphasized as essential for creating a competitive edge from it. Analytics is anticipated as one core component of future competitiveness as part of product and business models, and solely relying on externals limits an organization’s capacity to build maturity for this anticipated competitive environment. Further risks mentioned include the lack of the ability to create

Analytics enabled business ideas or loss of these ideas, loss of data and control over data usage, and loss of control over solution quality. Certain Analytics initiatives must be done internally, due to privacy, confidentiality, and data security concerns, or because regulations prohibit data sharing. Thus, scholars' recommendations (Lai et al., 2018; Sanders, 2016) to remain in the "comfort zone" of core competencies should be subject to critical consideration and careful assessment.

Since it displays an extreme position intended to broaden the insight generated from case studies, similar to the previous rival explanation, Rival 2 of Proposition 5 was rejected. Completely developing and sourcing Analytics internally limits the organization. Externals can be cost effective providers for solutions with high maturity for uncritical business problems. Regarding competitive advantage, their support can accelerate the process, reduce costs, reduce risk of failure, and introduce new ideas on problem-solving. As a critical side note from interviewees, not all externals can necessarily contribute these benefits, but market leading providers should. Organizations have different core businesses and competencies, and they should not disregard the development of innovative Analytics concepts and technologies happening outside their own organization.

Organizations should have full control over strategic initiatives and customer facing services, Analytics or other, but externals, if bound to confidentiality, can have an important impact on strategic initiatives by introducing additional ideas and information. Thus, Rival Explanation 3 is inconclusive. There was no consensus to be found in the case studies. Some strongly rejected the explanation, arguing for the vital importance of strategic initiatives, the risk of losing new revenue streams to co-creators, and different understanding of customer needs. However, other cases appreciated the use of externals for the innovative solutions that could be created in partnerships and acceleration of implementing strategic initiatives leading to first mover advantage.

While the case organizations represent leaders with relevant insight on this research, only a few LSCM organizations build internal Analytics expertise. Many intentionally take follower positions and, thus, source Analytics expertise completely externally. This does not contradict Propositions 5 since it has not been experienced that such organizations gain competitive advantage from their Analytics initiatives. Further, case organizations have even started to push competitors to use Analytics since they perceive this reluctance as a risk to the field

In summary, the proposition is rejected, since the proposition only covers parts of the rationale in the data. Rivals 1 and 2 are rejected and Rival 3 is inconclusive.

5.4.6 Data as a resource

Data as a resource was a controversial topic in the case studies. It is the core of Analytics, holding the insights that enable valuable opportunities, but it is also a source of challenges and frustration. Interviewees expressed their frustrations vibrantly: “because every customer says: ‘the data is there, it's great, it's no problem at all.’ It's not like that, it's never like that.” Data issues can impede its use for Analytics, including: (1) integration of data (different formats, timeliness, frequency, granularity, or data definition of business objects, missing context or technical accessibility), (2) data quality (missing annotation, incomplete data, uncertain correctness, errors from sensor failures), or (3) data management (ensuring data security, missing overview over data, unclear responsibilities for data quality and security). Further organizational issues can result in denied access to the resource, including: (4) protectionism (unwillingness to share data, missing trust between supply chain partners) and (5) infrastructure (evolved data silos, differing decision rules for similar data). These issues reduce the usability of the resource and the value of solutions, considering the repeatedly mentioned “garbage in, garbage out” principle. However, they concern handling and care of the resource and become less relevant with increasing maturity in Analytics due to standardization and improvement efforts driven by needs inside and outside of Analytics initiatives. The relevant issues arise from the insights held in the data resource. To generate insights from data to solve a business problem, two steps are necessary. First, data must be analyzed with quantitative methods and algorithms, which may not be able to uncover comprehensive insights about the entity the data was collected about. Second, the results from these methods must be interpreted for their relevance and impact on the business problem, which demands additional knowledge on context and domain that cannot simply be substituted. Thus, the full insight covered in the data might not be transferred to the business problem of an Analytics initiative. Further, data might not be collected for technological reasons, data security reasons, prohibition by law, and due to missing installations of sensors. Hence, insights may not be transferable completely with data as the carrier. Additionally, resulting from this and previously discussed evidence, all these activities of collecting, managing, and analyzing data and interpreting results are usually time, resource, and cognition intense, making the transfer of insights to solve a problem with data as carrier costly. This resembles the characteristics of tacit knowledge as explained in the KBV, and supports Proposition 6, again with supplementation.

An emphasized adjustment to Proposition 6 is the progress in methods and technologies, which results in decreasing costliness of extracting insights from the data. Further, in exceptions, costly Analytics cannot promise to extract insights that are valuable, and in other initiatives the extraction of insights is not costly, but the insights are valuable.

The extraction of insights from data being simple, as specified in Rival Explanation 1 of Proposition 6, was rejected. Analytics initiatives with simple to extract valuable insights for problems or organizations become fewer with increasing maturity of organizations in Analytics. Moreover, the process of insight extraction from data was explained to be cognitively effortful and time and resource consuming.

Evidence concerning Rival Explanation 2, which proposes that insight extraction from data does not lead to greater value than insight from human intuition, is inconclusive. The inconclusiveness centers around the ambiguity of the term “intuition”, which describes some “gut feeling” or guesswork but also human knowledge, experience, and access to information not represented in analyzable data. The latter consists of cases in which Analytics insights cannot exceed human knowledge, problems cannot be modeled, discoveries are irrelevant, analytical methods miss patterns, or data from different sources are inconsistent, leading to suboptimal decision support. However, there are also cases in which Analytics solutions exceed human knowledge and experience. After all, human knowledge and experience are often necessary to create valuable Analytics solutions in the first place due to understanding of interrelationships, sensemaking of data, or feedback guiding the problem-solving process. Combining human knowledge and experience with Analytics was reported to achieve the best business outcome, making Analytics dependent on humans’ abilities but not declaring human intuition as superior to Analytics.

The dependency on large volumes of data for valuable insights, stated in Rival 3, is also inconclusive. While small data can also create valuable insights, the data volume can be substantial for enhanced insight creation under certain conditions. The additional data volume must explain more aspects of the business problem, either from a greater variety that allows the explanation of more effects, or from more equivalent data but with higher diversity of observations. Resultingly, more precise solutions must be creatable, or new questions answerable. Further. the volume must be exploitable (technically manageable, with provision of results before the value of the insights degrades) and have good quality. Most importantly, and sometimes missing form Big Data discussions, the larger volumes of data only provide value if they fit with the problem. In contrast, if there are privacy or security concerns with the data, more data can result in higher risks.

Regarding LSCM, a complexity in analyzing data arises from LSCM being process focused resulting in according data creation, while classical IT systems are oriented to the structure of the organizations. Hence, analyzing the process can be challenging. Further, LSCM operates in dispersed locations. Thus, different markets of operations bring different business rules applied to the same data and generate differing insights. In established and grown organizations, the dispersed locations (manufacturing, storage, fulfillment), globally and locally, have been set up with heterogeneous and now outdated systems, which either prohibit data access or provide data that cannot be integrated, making the knowledge technically tacit.

In summary, Proposition 6 is supported, Rival 1 rejected and Rivals 2 and 3 inconclusive.

5.4.7 Deploying Analytics solutions

Evidence emphasizes a deployment of Analytics insight such that decision-making is supported in a consumable form, which accelerates the business process, is more relevant and appropriate to the decision, or enables users to consider a wider variety of business questions. The value from Analytics is eventually measured by the resulting business or process performance, since Analytics is supposed to result in better or faster decision-making. However, the desired value can be missed if deployment of insights is delayed or leads to wrong decisions because of missing consumability. A lack of consumability prevents users from accepting and using the solution or reduces productivity. Consumability is influenced by a variety of characteristics. The solutions should fit to the process and users by being intuitive for users and intuitive in regard of the process, available when needed, attracting attention for relevant situations (alerts, visualizations), reflecting business logic, and, if needed, allowing the use of preferred devices including mobile technologies. Complex decision-making becomes more consumable by reducing the steps to the decision, reducing decision-making effort especially under pressure, and making insights usable without deep analytical knowledge. For uncertain decision-making, consumability includes access to additional insights on demand and to the expected consequences of the recommended decision. In summary, solutions must be timely and appropriate to the business impact of supported decisions. Insights on the same problem for different user groups (e.g., maintenance vs. new product development) are consumed differently and require different deployments, underlining the need for involving users in the problem-solving process. This consumability is established by a deployment that is fitted to the process and users to ensure beneficial usage, reflecting the suitability of the knowledge integration mechanisms to the process and organizational characteristics for efficient knowledge integration. This supports Proposition 7, with subsequent adjustments.

Necessary clarifications must be made to adjust Proposition 7. First, consumability does not exclude training. Second, consumability is not the uniquely important aspect, since the deployed solution must also fulfill technical and legal requirements (scalable, secure, legally correct, licenses are paid).

Rival Explanation 1 for Proposition 7 describes the migration of decision-making supported by Analytics solutions into the responsibility of data scientists. This is rejected. The cases emphasized users must remain in the process and be enabled and empowered by appropriate solutions. The users have the necessary experience and knowledge for the processes, can interpret and identify the most appropriate decisions and actions given the insights, and should remain responsible for decisions and actions. Analytics solutions cannot cover the full decision-making process and tasks of users, which require understanding of the business environment, strong process related skills for which users are educated, and ideas to improve processes with methods outside the realm of Analytics, which data scientists cannot substitute.

Analytics products are intended to reduce user effort, including the automation of certain repetitive and less complex tasks. However, replacing the users completely, as stated in Rival Explanation 2, is neither desired nor technically possible, leading to rejection of the explanation. The intention is to reduce users' tasks that are time intensive but do not provide much benefit to users or organizations (e.g., manual data collection, manual data integration), while this study did not investigate whether this is in the interest of the user. The automation of decision-making requires a proven and established solution with consistently superior performance for the user and a backdoor process for eventual changes. In complex decision-making processes, such automation is often technically not possible but instead requires users' abilities such as ingenuity, creativity, and ability to interpret and understand the impact on the process, and to evaluate the best course of action. As also noted by Roßmann et al. (2018), human skills will remain necessary for decision-making. Automation cannot transform a business in the way a knowledgeable design decision by a human can do. However, certain jobs are becoming less attractive or require actions beyond human abilities, such that it becomes necessary to develop automated solutions. Further, Analytics solutions may lead to centralized decision-making or the ability to scale tasks and replace users in that way. Ironically, interviewees reported the increasing automation of analytical tasks.

As discussed above, users are increasingly enabled through self-service Analytics. This depends on Analytics products developed in Analytics initiatives to create solutions that provide access to relevant data – data democratization – and analytical tools fitted to the user. As Guerra and Borne (2016) describe, democratization of data implies easy access based on standardized metadata, access protocols, and discovery mechanisms. It is not practical to leave the generation of insight and solution deployment solely in the hands of the users, who receive the results from some analytical method, rejecting Rival Explanation 3. Self-service or self-sufficient Analytics (for the users) depends on the users' affinity for Analytics, their willingness to learn, and the complexity of the problem. Certain insight generation, self-sufficiently executed by users, contributes to building trust into Analytics solutions such as customization (change reports, build own apps) or further data exploration. This basically efficiently exploits users' knowledge on needed data, understanding of processes, and ability to interpret data and insights in context.

The field of LSCM displays an interesting occurrence regarding this proposition, because automation is a major aspiration, but not to cut jobs, as feared by automation opponents. The intent to automate is stimulated by the lean mindset, a central mindset of physical process optimization in LSCM, which focuses on reducing non-value-adding activities. Thus, automation intends to free employees from these, often repetitive, activities and provide more time for value-adding activities and innovating based on their expertise. The value of LSCM experts was strongly emphasized in the case studies and the irreplaceability of the experts' knowledge by automation was expressed repeatedly.

In summary, Proposition 7 is supported, and all rivals are rejected.

5.4.8 The responsibilities of the user

Insights from Analytics solutions must be integrated into business processes to result in decisions and accordingly taken actions. Similarly, discoveries must be operationalized by supporting decisions and (corrective) actions users are responsible for taking to improve business processes or eliminate inefficiencies. This seems rational, but is not always how users act. These decisions and actions from Analytics solutions are necessary to generate return on the investment. Unused solutions may result in additional investments, since the business problems appears to be unsolved. As one interviewee described: “if your weather forecast says rain, but you don't take an umbrella and get wet, you can't blame the weather forecast nor the umbrella manufacturer”. The purpose of Analytics is not analyzing data – as already indicated in the literature (Chae, Yang, et al., 2014). The purpose of Analytics is to improve decision-making and business processes through integrated, Analytics-enabled support or automation, provided Analytics is the tool in an organization’s toolbox that achieves the desired solution with superior performance or cost efficiency. Further, integration includes process changes by allowing users to collect feedback on the solution’s performance, such that transparency of results and long-term improvements are enabled. Since this underlines the importance of applying the insights from Analytics solutions during the value creation process of transforming input to output, Proposition 8 is supported with subsequent adjustments.

As clarifying adjustments, the method of integration and the level of change of the business process strongly depend on the insights, such that discoveries in presentations and reports with longer periods of validity are integrated differently as compared to alert systems. Further, the solution must be created such that integration into the business process is possible, and, in accordance with the results of Srinivasan and Swink (2018), the business processes may have to be stabilized first such that integration is possible. It should not be implied that all new insights are dominant over previous decision-making. The solution from an Analytics initiative may just provide additional insights for decision-making in the process.

If a deployed solution is established and feedback returned, users should not evaluate whether to use or to ignore the decision support recommendation or assistance because, for example, it does not fit their intuition. Thus, Rival Explanation 1 to Proposition 8 is rejected. However, such an evaluation would be part of the solution’s refinement and validation during deployment, which benefits from users’ knowledge and experience. Further, decisions themselves are evaluation processes, which are supported by Analytics solutions and usually include further sources of information. For making the decision, users should not blindly follow the actions recommended by Analytics solutions, since these could also include distortions (e.g., failing sensors). But risk is no excuse for generally or conveniently ignoring. Again, critical business information might not be covered by available data and models and thus the Analytics solution may be overruled. The critical information available to the user must be sound. Further, there might be additional decision options that are severe and purposefully unavailable in the Analytics solution. However, this argument applies only in certain situations.

Interviewees clearly emphasized that users should not recalculate the results provided by Analytics solutions. Thus, Rival Explanation 2 is rejected. Solutions should usually be consumable, reducing the needed mathematical skills of the users. The effort required to recalculate the results would likely eradicate the intended time benefits and would be scarcely manageable by the user, especially with complex calculations connecting several models. However, change aversion results from lack of understanding. Hence, to build trust, how the solution works and generates the insight should be explained to users. This might include recalculation in some form.

While transparency can reveal mistakes, it should be used as a chance to learn instead of building pressure. Handled as an opportunity for learning and supporting users, Analytics is perceived as beneficial and builds demand. Used to apply pressure, solutions will not be accepted and applied, and data will not be shared willingly. Thus, Rival Explanation 3 is rejected. Transparency should be created while remaining ethically sound and ensuring users' privacy with established data security. Organizational authorities should monitor this, while also clarifying and creating consensus about ethics and privacy, setting up rules to follow and enforcing them ("data governance"), and providing users with understanding about data collected related to them, the reasons for collection, and how to take control of their own data. A rising need for governance was foreseen by Carillo (2017) and his demand for research attention is supported by this research. Increased transparency should be beneficial for organizations and users, and benefits must be communicated to users. Otherwise transparency could become a source of fear (blaming, loss of power, job automation). However, limitations should be reasonable and not overprotective or generally refuse transparency. Transparency can be achieved without any relation to users, and data on users can be separated from data regarding the subject of analysis. Making organizations transparent is needed for business success, safety, and risk management, and to identify intentional wrongdoing.

In LSCM, the responsibilities described in Proposition 8 result directly from the business problems tackled. The aspired transparency on changing conditions does not affect the situation for the organization. The situation is changed when users take decisions and actions accordingly, such as redistributing resources, rescheduling, or reordering. Faster response and broader insights on the changed conditions with their consequences should increase available decision options with resultingly better outcome for the organization. However, evaluating the options, taking decisions, and triggering actions is the user's responsibility.

In summary, Proposition 8 is supported, and all rivals are rejected.

5.4.9 Organizational factors of Analytics initiatives

Several organizational factors are identified in the evidence, which enhance the value generated from Analytics. However, while these are related to a culture of open and positive interaction with data, this culture was neither explained to be exclusively driven by data nor was it named a data-driven culture. Further, factors derived from the Analytics literature incompletely cover the organizational factors essential to enhance value from Analytics. Thus, Proposition 9 is rejected. However, the collected organizational factors strongly resemble the enhancing factors of knowledge integration of the KBV. First, common knowledge resembles organizational factors such as knowledge about available data to solve business problems ("data literacy"), understanding of the results and risks of analytical methods, and understanding (and appreciation) of the work behind Analytics. Second. frequent and varying knowledge integration resembles two differing groups of organizational factors in the evidence. Frequency occurs through willingness to share data, willingness to use Analytics, emphasizing ("evangelizing") achieved and potential value from Analytics, and providing time to work with Analytics or on ideas for initiatives. The variability of knowledge integration occurs through value enhancing organizational factors of openness to ideas, creativity, curiosity, and openness to consider its own actions being possible sources of mistakes. However, the value of Analytics is enhanced by further organizational factors outside the scope of Analytics or the KBV’s knowledge integration, such as willingness to cooperate, embracing change, holistic thinking, or a mindset fitting to the customer. These do not fit the proposition. Third, supporting structures resemble organizational structures for data sharing, structured processes of Analytics, infrastructure for Analytics, and alignment of Analytics with business goals. Interviewees recognized that not all factors can be present in an organization, but setting them as goals will lead an organization in a direction in which the value from Analytics is enhanced.

Rival Explanation 1 of Proposition 9 – of all users needing to be data scientists or being comparably educated – was rejected as a doubtful future scenario, as already stated by Roßmann et al. (2018). Users need certain knowledge about Analytics to avoid fallacies, understand the work behind and implications of Analytics, and to create more rich ideas for business problems to tackle. However, this level is far from the abilities of data scientists. Interviewees anticipate an imminent rise of the need for users in business processes who are better educated on Analytics, but only to allow easier interaction with data scientists and for using Analytics solutions as part of their empowerment. The need for users to embrace innovation is far greater, which involves accepting data scientists as vital team members for collaboration along with other vital members.

The second rival explanation was rejected as well, since case studies clearly emphasized Analytics' value to be enhanced by the organizational culture. However, contrary to expectations, a culture is required that embraces collaborative thinking and acting, embraces innovation, and is open to change. An innovation culture was specifically and repeatedly mentioned, supplemented by an agile mindset, entrepreneurial mindset, rapid testing of ideas, and involvement of users and customers in design processes.

Appropriate critical reviews of Analytics solutions are considered beneficial, and for some solutions, critical feedback from observing them in process provides improvement potential that is hard to achieve before deployment. As discussed above, engineering knowledge, a practiced way of thinking and doing business, or informed decision-making based on older and simpler (analytical) methods can provide appropriate criticism and suggestions that should not be disregarded. However, an intuition-based culture should be avoided that ignores Analytics results, treats Analytics with disregard, and mistrust or rejects any form of change. Thus, Rival Explanation 3 is rejected. Mistrust or demand for unrealistic certainty levels of solutions will delay the use of solutions and result in missed opportunities.

In accordance with Proposition 5, an organizational factor in a large share of LSCM organizations is a missing appreciation for resources outside the physical "bread and butter" processes. Behind the leaders such as the case study organizations, there is a field of followers that treat IT as "hygiene factor", and which cannot build Analytics capabilities on that attitude.

In summary, all explanations, propositions and rivals have been rejected.

5.4.10 The long-term usability of solution in Analytics initiatives

An Analytics product meant for continuous use is not finished after deployment. It must be maintained and shows constant need for adjustments because of newly available data and data sources, needs and feedback from users, degradation of solution performance over time, and evaluation of achieved business outcome. As part of deployment and as described above, there is usually an adjustment phase of the solution to the business process. Maintenance comes after this adjustment and is necessary to assure performance through monitoring and quality control ("Analytics on Analytics"), and adjustments to changes in the technological ecosystem (e.g., the solution hosting system or systems the solution is interacting with). Further, maintenance involves extending existing solutions by including changes present in more recent data like new patterns, new anomalies, or different behavior of processes and customers triggered by the Analytics solution or market and societal changes, which shift optimal points and priorities of recommended actions. Solutions are likely transferred or scaled with smaller changes to new user groups with similar business problems. Further, solutions will be overhauled or replaced if new ideas or newly tested analytical methods on solving problems migrate from more recent initiatives to the focal solution or if the promoted and visible value and benefits from a solution induce demand for additional features or ideas for improvement. Interviewees observed a surge of new ideas for Analytics initiatives once users had been exposed to helpful Analytics solutions and emphasized the ongoing opportunities for improvements in organizations, which can be supported by Analytics. This resembles the continuous renewal of capabilities to sustain competitive advantage specified in the KBV of extending the capabilities to include new knowledge and using existing knowledge in new capabilities. This provides support for Proposition 10. However, discoveries usually experience little to no maintenance.

Rival Explanation 1 of Proposition 10, which states that Analytics solutions are stable and, thus, represents the opposite of Proposition 10, is rejected. As discussed above, Analytics solutions need regular adjustments to internal and external developments along the solutions' lifecycles. A multitude of aspects of solutions can change including input, functionality, or the business and technological environments of the solutions, which will influence their performance.

Analytics solutions will not be adapted to individual users. Solutions are developed for certain roles, and if roles do not change in objective criteria or tasks, resulting in a change of users' behaviors, there is no need for user-based adjustments. Thus, Rival Explanation 2 is rejected. If new users are introduced to an Analytics solution, because the solution is newly developed or the users newly hired, they will usually be trained. Too much individualization creates chaos but there should be room for personalization for consumability. However, users' requests will be considered for solution improvement and building the trust of users. But these considerations include prioritization and removal of features that turned out bad.

Finally, Rival Explanation 3 of solution replacement by newly available technologies is rejected. New technologies will not automatically trigger adjustments. The choice of technologies is driven by the business problems and a change of technologies for solving a business problem requires justification by improved performance or fit to requirements, exceeding the cost of migrating to the technology. Migrating solutions to new and appropriate technologies is likely if existing technologies present a bottleneck. In addition, a technology's cost benefit evaluation changes as the technology matures, becoming less costly or addressing more needs. Cost evaluation should additionally be done for the long-term and with anticipation of future requirements to stay on track with the competition.

Regarding the decentralization of LSCM functions due to globally operating supply chains, interviewees emphasized the need to have a vision about scaling a solution in development to similar supply chain functions in other locations after it has been tested and validated. This should avoid these functions having redundant development efforts or creating isolated solutions.

In summary, Proposition 10 is supported, and all rivals are rejected.

5.5 Conclusion

This research has developed an explanation of how Analytics generates competitive advantage for organizations based on the knowledge-based view and using the example of Logistics and Supply Chain Management, as illustrated in Figure 25. In short, managers need to identify business problems with tangibly beneficial solutions that are complex or business critical. They select expertise, creativity, and data from internal experts and acquire it from experts from the market, and manage the experts to find the solution. Within the bounds of a structured initiative, this team of cross-functional experts

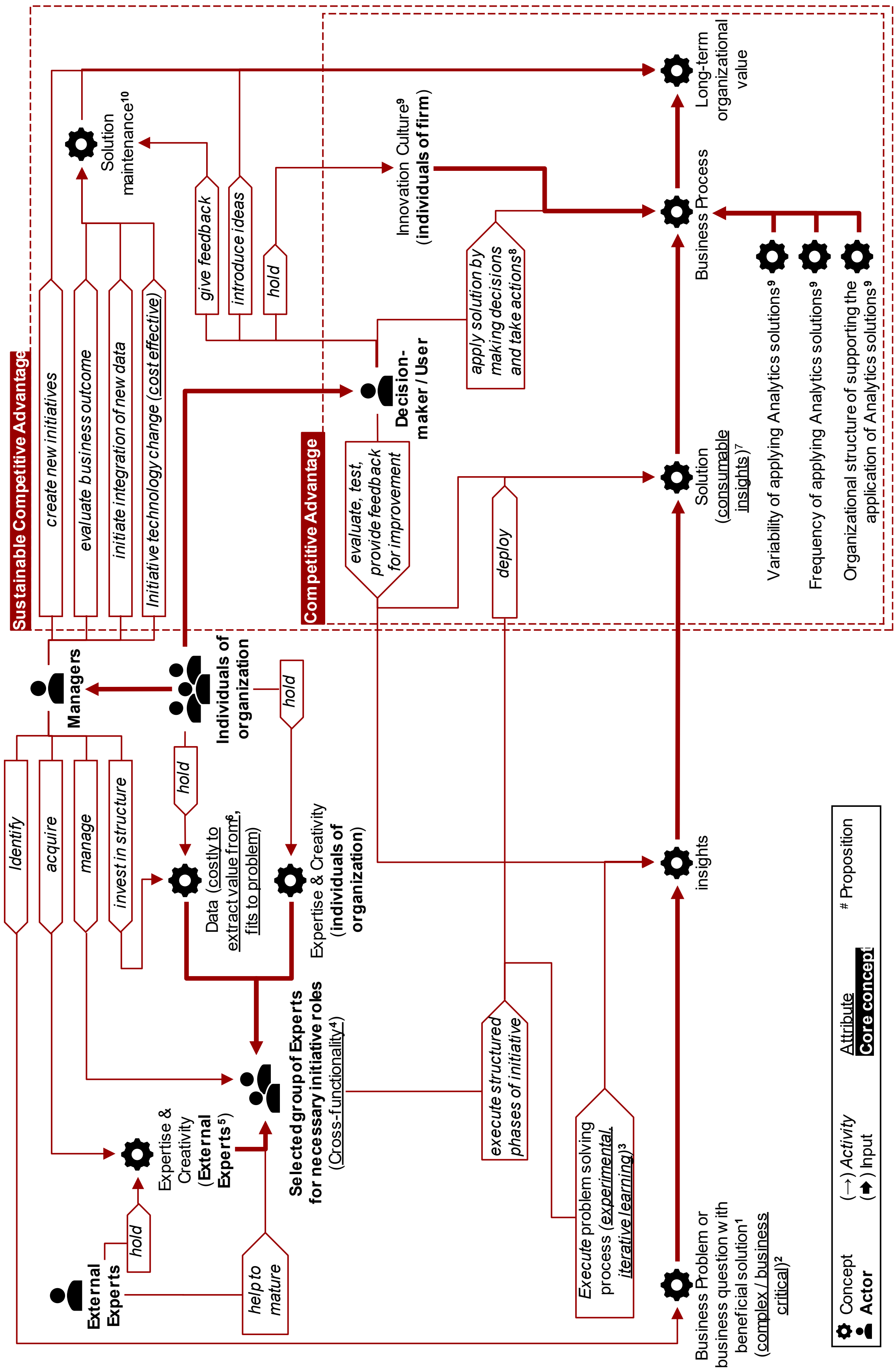

Figure 25: Creating competitive advantage from Analytics

solves the problem experimentally and iteratively by presenting intermediate insights extracted from data to users for evaluation and directions. If the intermediate insights fulfill the performance criteria of the users, a consumable solution is developed that is appropriate to the decision-making of users and the process requirements for decision-making. The users must integrate the solution into their decision-making process during value creation in the business process and make decisions and take actions accordingly. The impact of integrating Analytics into the value creation process is enhanced by the variability of applying Analytics solutions, the frequency of their use, and supporting organizational structures, as well as a culture fostering innovation and welcomes change. Analytics solutions, which are created to solve complex and business critical problems that are ahead of the problems the competition has solved and are applied frequently and amongst a variety of such solutions in the value creation process, provide value that has the potential to generate competitive advantage to an organization. To sustain such competitive advantage, users need to provide feedback on deployed Analytics solutions and introduce further ideas for new solutions. Based on the feedback, evaluation of business outcomes, and collection of new data, managers must initiate maintenance and advancement of deployed solutions. Further, they must create new Analytics initiatives from the ideas.

Hence, Analytics presents a manifestation of knowledge-based generation of competitive advantage. This research emphasizes it as supplement to the organizations' toolboxes that is suitable for problems with relevant knowledge held in data or for which data can be collected – which are becoming more and more common. It does not present a single standing way of generating competitive advantage for most organizations. As with any tool, the value generated from it depends on the right use and, further, it does not guarantee competitive advantage.

This explanation was concluded from eight confirmatory case studies, which provided evidence to support or reject propositions based on the resemblance of the KBV with the Analytics literature and rival explanations to these propositions. The extensive data collection and analysis resulted in eight propositions being supported, one proposition being rejected because of an incomplete explanation, and another proposition being rejected. However, due to the research design, the collected evidence allowed to derive an explanation of how competitive advantage can be generated from Analytics. The rival explanations, mostly rejected, nevertheless supported adjustments and demonstrations of exceptions to shape the explanation.

5.5.1 Theoretical implications

This research contributes to two research streams. It provides supporting evidence for the validity of the research stream of the knowledge-based view due to its manifestation as the lifecycle of Analytics initiatives. The necessity of not just holding resources but using them in the right way in the value creation process is strongly supported by the evidence. Thus, any technology and concept must be evaluated on the use cases it provides and the problems it can solve in organizations. It should not be hyped for a potential value that cannot migrate into the processes of organizations. The importance of the effort of integrating knowledge into the value creation process, the role of individuals in the organization, and of the integration process as formulated in the KBV are strongly supported by the evidence. The moderating factors are prone to be overlooked in consideration of the necessary characteristics of the resources.

The role of the market as knowledge source was discovered to be broader than described in either the KBV or Analytics literature and should be investigated further. Research must take a deeper look at the changing role of the market in this digital economy. Valuable knowledge can be converted ever faster into micro-products and services and, thus, be sold to organizations, which can integrate the knowledge into their processes. Competitive advantage could be generated from a meaningful combination of market sourced micro-products and services to generate a unique and advantageous value creation process.

For the research streams of Analytics, a theoretical foundation for the effectiveness of best practices has been provided. This foundation provides explanations for the superiority of certain practices, which are experienced as working better than others. Further, an emphasis on cost-effectiveness was introduced, presenting Analytics in the context of restrictions of mindful application and prioritization – to make data-driven decisions about the methods used for data-driven decision-making. In addition, for this data focused field that appears to be very technical, the reliance on creativity and ideas has been discussed and should receive further research attention regarding how to identify and support the right creative talent in organizations.

Regarding cross-functional problem-solving with Analytics, the role of a mediator should be investigated further. While the role of translation between different experts has been declared as the mediator's limit, this interpretation might be under-valued. Further, this mediator might be specialized in methods to stimulate the generation of ideas and induce additional ideas from experts who hold specialized knowledge but are not using it at a full capacity on a problem.

Research should further evaluate the use of agile methods for the research process. Short but frequent iterations with the audience the research wants to address might provide more impactful research to this audience. However, this is not intended as an argument for discarding scientific rigor, but a paradigm shift from thinking about how to address the audience, to a process of frequent exchange with the audience.

Regarding LSCM, this paper identifies the need for further research on the impact of digital and Analytics-based business models on LSCM. This paper has perceived a disregard of LSCM organizations for the risk from such business models, while they could eventually eat up profitable business and margins from LSCM organizations and force these organizations' services to a commodity status. This potential development should be studied further.

Finally, further research is necessary on the beneficial integration of visibility into LSCM processes and the changing decision landscape. While the visibility is increased, it may not be beneficial without the ability to exploit it and opportunities to act on it. To gain this ability, extensive change of the supply chain might be necessary.

5.5.2 Managerial Implications

This research provides guidance for the execution of Analytics initiatives derived from the domain of LSCM, embodied in the subfield of Supply Chain Analytics. Managers are directed to base their pursuit for advantages, including competitive advantages, not just on analytical methods, but also on the problems chosen on which to use the analytical methods. To find these problems, managers must foster curiosity and the generation of ideas among employees. To ensure obtaining value from the solutions, they must build the trust of the intended users in the solutions and establish a culture that embraces change.

In this regard, this study advises not to glorify data scientists. While the role is new, scarce, and has potential to be impactful on organizations, it is strongly dependent on the other experts of the organization. An image of the data scientist as jack-of-all-trades who naturally supersedes the process experts by building data driven solutions devalues these experts and negates their willingness to cooperate. Indeed, the cost benefit ratio of such a jack-of-all-trades is a fallacy, because this quite expensive multi-talented individual has a finite workload capacity in which tasks outside mathematical and analytical specialization would have to be accommodated.

This study demonstrates that Analytics does not just comprise the analytical. Managers interested in using Analytics must be aware of iterative ways to build the solutions with cross-functional teams, especially including the intended users, to overcome the difficulty of extracting insights from the data and to ensure the deployment and use of the solution. They may contract providers to help them build maturity in Analytics but also for the purpose of getting access to knowledge they only need in rare instances and as an "extended workbench". Deployed solutions should be maintained to ensure performance and technical functionality and for improvements based on constant feedback and inspired by other initiatives.

There is a causality dilemma, since a good data infrastructure is required to identify beneficial use cases, but beneficial use cases are required to motivate investments into data infrastructure. Evidence suggests managers should make courageous investments in infrastructure to set a basis for valuable Analytics initiatives and to substantiate the desire to increase the use of Analytics in their organizations. Presenting and substantiating this desire is important to spark ideas for use cases and problems to tackle. As observed by the interviewees, asking the people in the processes and encouraging them to generate ideas will almost certainly result in Analytics initiatives that can create value in the organization and is the way to mature in Analytics and tackle more complex Analytics with a competitive edge.

Regarding LSCM, organizations which are already conducting projects in cross-functional teams that bring all relevant functions to the table and work towards an end-to-end supply chain vision should consider exploiting this cross-functionality further. This study has highlighted the value of marginal knowledge, which can be operationalized by introducing additional experts into such cross-functional teams to generate new ideas and approaches.

This study emphasizes building a culture that supplements the strong pride in the physical process management and optimization skills with an appreciation of supporting functions such as IT and Analytics. This is certainly not routinely the case with market leaders, but the LSCM field is composed of a broad range of small and medium organizations, which can benefit from these supporting functions as well as need to be open to them.

5.5.3 Future research and limitations

Considering the evidence collected in this research, some aspects present a strong demand for future research. First, it is necessary to create guidance for data governance, investigate appropriate analytical actions that harm neither ethics nor privacy, systematize practices to ensure privacy while enabling analysis of organizational activities, and provide reflected discussions on ethical Analytics. Second, willingness to change is a long-lasting issue, which requires means for managers to investigate and overcome resistance to change in order for initiatives to be effective. Third, while the estimated percentage of today's jobs likely to be automatable is very large, this research indicates that this ability might not be used, and control may be kept in the hands of users. Research is necessary to understand which decisions managers will not give out of hand and for what reason, to provide a better projection of the future of automation and allow a longitudinal observation to reveal whether these reasons are sustained or change over time.

There are limitations that apply to this research. This research was conducted on the example of LSCM and, consequently, provides a generalization within the bounds of the LSCM domain in Germany. This research should be recreated for other domains, with an emphasis on the factors that distinguish each domain in the use of Analytics. There has been limited access to interviewees, which has been compensated with an extensive review of documents. The number of experts available for this investigation was limited due to the novelty of Analytics to a broader range of domains and organizations. Further, these experts are busy and work on topics for which disclosure is undesired. In addition, the number of case studies could have been increased for increased validity. Finally, while confirmatory case studies are rarely observed in the scientific literature as opposed to survey research for collecting confirmatory evidence, the approach was chosen to gain the opportunity to shape the explanation in focus. Thus, further quantitative confirmatory methods might be employed to validate the results.

6 Overcoming Barriers in Supply Chain Analytics – Investigating measures in LSCM organizations

While Supply Chain Analytics shows promise regarding value, benefits, and increase in performance for Logistics and Supply Chain Management (LSCM) organizations, those organizations are often either reluctant to invest or unable to achieve the returns they aspire to. This article systematically explores the barriers LSCM organizations experience in employing Supply Chain Analytics that contribute to such reluctance and unachieved returns, as well as measures to overcome these barriers. By using Grounded Theory through 12 in-depth interviews and Q-Methodology to synthesize the results, the article derives core categories for the barriers and measures, and their impacts and relationships are mapped based on empirical evidence from various actors along the Supply Chain. Resultingly, the article presents the core categories of barriers and measures, including their effect on different phases of the Analytics solutions life cycle; the explanation of these effects; and accompanying examples. Finally, the article provides recommendations for overcoming the identified barriers in organizations.

6.1 Introduction

The business of Logistics and Supply Chain Management (LSCM) is changing rapidly based on new technologies and consumer trends that demand new and broad digital capabilities (Monahan et al., 2017). The phenomenon that is taking hold of this business, transforming it, and that demands action from the organizations in the market, is digitalization (Chung et al., 2018). One of the inherent effects of digitalization is the constant growth of data, describing all sorts of aspects of the world and, thus, possessing potential insights about it and opportunities to act on those. This growth is not expected to halt or decelerate but to accelerate exponentially – a recent study estimates a growth of the global datasphere from 33 zettabytes in the year 2018 to 175 zettabytes in the year 2025 (Reinsel et al., 2018).

To leverage the growth of data and the opportunities of digitalization, the studies mentioned above emphasize the use of Analytics. Analytics is the use of various quantitative, explanatory, and statistical methods on extensive amounts of data (Davenport and Harris, 2017). When focused on the context of Logistics and Supply Chain Management, it is specified as Supply Chain Analytics (SCA) (Souza, 2014).

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Scholars have established that SCA helps to improve organizational and supply chain performance, increase efficiency, reduce supply chain costs, and contribute to competitive advantage (Chae, Yang, et al., 2014; Dutta and Bose, 2015; Sanders, 2016; Trkman, 2010; Wang et al., 2016).

The implementation and application of SCA is, however, an immense challenge for organizations. Scholars and organizational reports alike have demonstrated a variety of barriers organizations face and the resulting effect of low implementation rates. Scholars have presented barriers ranging from management failures and lack of analytical knowledge to unwillingness to commit IT resources (Dutta and Bose, 2015; Kache and Seuring, 2017; Lai et al., 2018; Richey et al., 2016; Sanders, 2016; Schoenherr and Speier-Pero, 2015). Organizational reports highlight the barriers of cost, insufficient data, and not achieving the benefits aspired to (APICS, 2015; Pearson et al., 2014; Thieullent et al., 2016).

However, these studies did not explicitly intend to explore such barriers but identified them in addition to their research objectives. And, despite these studies clearly implicating the existence of various barriers, scholars in the field of LSCM have rarely addressed the topic of measures to overcome these barriers. An exception is the study of Schoenherr and Speier-Pero (2015), who provide some insight on factors contributing to the successful implementation of Analytics in LSCM. However, research on practices and measures has concentrated on the research field of Analytics in general. As a result, there has been no investigation of whether LSCM employs specific measures, which measures are most relevant for LSCM managers, and what impact they have. Thus, this study intends to take a specific look at barriers occurring in the field of LSCM and identify which measures and practices are being applied to overcome these barriers. This research is intended to support Logistics and Supply Chain managers concerning directions in which to go forward with SCA in a successful and impactful manner and support the transformation of their supply chains into the digital age.

In particular, this study seeks to contribute to the following research objectives:

RO1: Depict the organizational barriers that appear when companies initiate, perform, or deploy SCA initiatives within the organization.

RO2: Derive organizational measures that seek to cope with the depicted barriers.

In pursuit of these objectives, 12 in-depth interviews were conducted with different actors along the supply chain including suppliers, OEMs, retailers, and Logistics Service Providers, as well as additional Analytics providers with strong experience in LSCM. From the exploratory and extensive interviews, the study identified the barriers to initiating SCA initiatives, applying SCA, and deploying SCA solutions and derived and the organizations' measures for coping with such barriers. The collected data was analyzed using the Grounded Theory approach (Strauss and Corbin, 1998). This approach was supplemented by the Q-Methodology (Brown, 2004; Valenta and Wigger, 1997) to derive a theoretical framework of measures and barriers in SCA, mapping barriers and measures of SCA initiatives and their relationships. This contribution, in terms of systemizing barriers and measures, extracting core categories, and identifying proposed relationships, provides an important basis for further deductive research.

The remainder of the article is structured as follows. Section 2 provides an overview of the relevant theoretical background to this study. Section 3 presents and details the methodology. Section 4 contains the results and their discussion. The conclusion, including implications, further research directions, and limitations, is presented in Section 5.

6.2 Theoretical Background

To overcome barriers that prevent the successful use of SCA solutions, this section introduces SCA and its previously documented barriers. Further, this section presents the recommended practices discussed in non-domain-specific Analytics literature as a preliminary analysis of available measures.

6.2.1 Supply chain Analytics

SCA is understood as the domain-specific application of Business Analytics (or Analytics), which is "concerned with evidence-based problem recognition and solving that happen within the context of business situations" (Holsapple et al., 2014, p. 134). In organizations, it is applied by analysts ("Data Scientists") using the most advanced and complex tools and methods (Davenport and Harris, 2017) or by process experts in the form of self-service Analytics exploiting the accessibility of Analytics in respective software for self-service (Beer, 2018). Analytics is an essential component of generating value from Big Data (Gandomi and Haider, 2015). Analytics has been reported to increase decision-making effectiveness, can generate organizational agility (given a fit between analytics tools, data, people and tasks), and can contribute to providing competitive advantage (Cao et al., 2015; Ghasemaghaei et al., 2017; Ransbotham et al., 2015).

SCA is specific to the domain of LSCM. LSCM is concerned with efficiently integrating the actors of the supply chain (suppliers, manufacturers, logistics service providers such as warehouses and transportation, retail) such that products are manufactured and distributed to the customer in the right amount, at the right time, at the right quality, and with system-wide minimal cost (Simchi-Levi et al., 2003). As a pivotal perspective to the definition based on actors and objectives, the definition of Christopher (2011) introduces the various activities and managed entities of LSCM. These include management of procurement and movement and storage of products in the different stages of their life cycles as materials, parts, and finished inventory. While the multi-objective trade-off under the influence of various actors, tasks, and entities already indicates the need for advanced methods to support decision-making, further aspects increase this need. Dynamic vertical, horizontal, and diagonal interactions among actors create hard to control complexity (Dittfeld et al., 2018), complexity increases the occurrence of disruptive events and, thus, operational and financial risks (Bode and Wagner, 2015), and due to the focus on the customer, common methods for managing disruptive risks from other domains are potentially a poor fit to LSCM (Heckmann et al., 2015). Further, besides disruptive events, volatility results in further mismatch of supply and demand (Nitsche and Durach, 2018), adding to the need for advanced methods to support decision-making.

SCA caters to the various decision-support needs of LSCM as it exploits the variety of Analytics methods for the multitude of issues (Souza, 2014). Thus, it is concerned with applying quantitative and qualitative analytical methods to recognize and solve problems evidence-based in the context of LSCM (Herden and Bunzel, 2018; Souza, 2014; Waller and Fawcett, 2013). In this regard, SCA helps to measure and monitor performance, understand and control poor performance, and improve performance (Chae, Yang, et al., 2014; Trkman, 2010; Wang et al., 2016). However, with the variety of tasks requiring support come a variety of applications that are hyper-specialized and also provide a challenge for organizations in LSCM (Sanders, 2016). Further, adoption of SCA in organizations in LSCM is slow, unwillingness to share data with supply chain partners is widespread, and organizations experience barriers (Brinch et al., 2018; Kache and Seuring, 2017; Schoenherr and Speier-Pero, 2015).

6.2.2 Barriers of Supply Chain Analytics

In this section, barriers to adopting and employing Analytics are reviewed. Several studies have discussed individual barriers in the domain of LSCM. However, these barriers are widely spread across studies with no study systemizing them or exploring barriers explicitly to create a comprehensive catalog. The presented literature overview is intended as a basis for the data collection. This literature overview is limited to the field of LSCM.

Following the cycle of an adoption process, an early barrier to adopting Analytics is the approachability of Analytics. Efforts to adopt and employ Analytics may be slowed down by a lack of consensus regarding the terms surrounding the concept of Analytics and the subsequent confusion (Kache and Seuring, 2017; Richey et al., 2016) as well as the perception of complexity and the difficulty of its management (Lai et al., 2018; Schoenherr and Speier-Pero, 2015). This is accompanied by a constant change of technologies and methods, which organizations would need to be able to keep up with (Sanders, 2016; Wang et al., 2016). Further, managers see the lack of LSCM specific solutions as a barrier (Schoenherr and Speier-Pero, 2015). Sanders (2016) describes this inability to adopt analytics due to overwhelming complexity as "Analysis Paralysis."

When approaching Analytics despite the perceived complexity, organizations in LSCM encounter a lack of experience of employees in Analytics and utilizing data (Sanders, 2016; Schoenherr and Speier-Pero, 2015). As opposed to the paralyzing complexity described above, the missing literacy concerning data and Analytics is expressed in missing knowledge and creativity. The lack of knowledge about how to approach and utilize data has been repeatedly stressed in the literature (Brinch et al., 2018; Kache and Seuring, 2017; Oliveira et al., 2012; Richey et al., 2016; Sanders, 2016; Schoenherr and Speier-Pero, 2015). This includes the identification of data most suitable for Analytics, understanding which data is useful and which is useless, experience with relevant technologies, ideas about what to do with the available data, knowledge on how to transform data into information for decision-making, and how to drive the supply chain with data. Oliveira et al. (2012) emphasize organizations' lack of roadmaps on using data and information even after systems for data collection have been set up. A further hindrance in this context is the inability to clearly point out how value in terms of the business objectives is generated from Analytics, and thus to sell Analytics initiatives to key stakeholders (Kache and Seuring, 2017).

To adopt and employ Analytics, resources are needed. Labor resources comprise the first form of resource identified in the literature as creating challenges for organizations in LSCM. One study reports time constraints as a primary barrier (Schoenherr and Speier-Pero, 2015), indicating the lack of time to get familiar with Analytics and relevant technologies as well as to execute initiatives in addition to daily business. Zhu et al. (2018) emphasize the time-consuming effort of getting Analytics solutions into production (meaning implemented and used in the value creating process), which might consume time from a variety of employees and hinder parallel initiatives. In addition, some labor requirements for Analytics present a challenge for LSCM organizations in themselves. The literature emphasizes a lack of employees in LSCM organizations to handle and understand data, Analytics software, and IT systems, as well as being able to interpret the Analytics results (Ramanathan et al., 2017). However, Kache and Seuring (2017) report that LSCM managers lack an understanding of what skills the required employees need to possess, leading to problems in recruiting these employees.

The second form of resources needed is monetary investment. The cost of solutions available on the market, the cost of getting the necessary raw data, and systems integration (of the focal organization and its partners) are named as barriers to adopting Analytics (Richey et al., 2016; Sanders, 2016; Schoenherr and Speier-Pero, 2015; Srinivasan and Swink, 2018). In addition, the returns from the investments and the benefits are hard to predict and unclear in advance. Thus, it is hard to estimate the breakeven point (Oliveira et al., 2012; Richey et al., 2016; Sanders, 2016). Furthermore, scholars highlight the problem of attribution of any performance increase to the investment in Analytics. They present issues of quantifying benefits, attributing benefits to Analytics or process changes, and time lags between implementation and identifiable performance increase (ramp-up) (Oliveira et al., 2012; Ramanathan et al., 2017; Trkman et al., 2010). In this regard, scholars have referenced the “IT productivity paradox,” as discussed by Brynjolfsson (1993), which presents the paradoxical situation of researchers not being able to measure a productivity increase from IT while organizations were increasingly investing in it (e.g., because performance increase is not measurable with their usual performance measurement or because of time lags).

To employ Analytics, usually several data sources have to be combined to solve complex business question (continuously). However, the issue of integrating systems in a diverse and incompatible IT landscape impedes the integration of data sources. LSCM managers reported a lack of integration of existing systems to scholars, due to evolved (rather than designed) environments with specialized systems for the various business units or due to legacy systems not intended for data exchange (Kache and Seuring, 2017; Ramanathan et al., 2017; Richey et al., 2016; Schoenherr and Speier-Pero, 2015). Scholars have emphasized that the issue is particularly present when Supply Chain partners with unaligned systems (fragmented systems with varying maturity) are expected to combine data sources (Kache and Seuring, 2017). Mistakes in this integration of systems can lead to inaccurate results and wrong decisions (Oliveira et al., 2012).

The supply of data is another major barrier to the adoption and employment of Analytics in LSCM. First of all, a lack of data or a lack of timeliness in providing the data has been reported as hindering (Hazen et al., 2014; Sanders, 2016; Schoenherr and Speier-Pero, 2015). Hazen et al.(2014) have particularly stressed the issue of insufficient data quality in general, which other scholars have confirmed, expanding the issue to having different quality levels controlled by different employees (Chae, Yang, et al., 2014; Richey et al., 2016; Srinivasan and Swink, 2018). Hazen et al. (2014) further stressed lack of means for measuring data quality, controlling data quality, and the persistence of bad quality data as input to Analytics until they are actively removed (since they are not consumed as opposed to other inputs). Further scholars added inexperience in assuring data quality to the list (Roßmann et al., 2018).

Having access to data comes with the issue of responsibility for that data, which can limit its usability for Analytics. Handling customer data alongside the organization's own data brings the responsibility for organizations in LSCM to ensure data privacy and data security (Kache and Seuring, 2017). Moreover, access does not equal ownership. Data ownership and the associated rights to data can be missing or unclear (Ramanathan et al., 2017; Richey et al., 2016).

To gain access to relevant data from supply chain partners or the right to use the data from partners for Analytics, their collaboration on data and Analytics is needed. However, several scholars present the issue of unwillingness of supply chain partners to participate in data sharing or its dependency on the provision of incentives and security (Kache and Seuring, 2017; Roßmann et al., 2018). Partners may want to, and should, keep certain data confidential (e.g., for legal reasons), but they also keep their data to themselves because of lack of trust and fear of losing control over their data (Kache and Seuring, 2017; Richey et al., 2016).

If all the barriers above are somehow overcome, the use and subsequent benefits of Analytics solutions in LSCM organizations are not assured. Scholars report issue with the mindset of employees regarding Analytics solutions. The employees may not want to use new, Analytics based systems, do not show openness towards them, and are not eager to change their culture (Dutta and Bose, 2015; Ramanathan et al., 2017; Schoenherr and Speier-Pero, 2015). Richey et al. (2016) specifically discuss how employees in LSCM value relationships and trust-based business generation, which they do not want to sacrifice for data driven solutions.

Another barrier to the adoption and employment of Analytics in LSCM can be the physical process assumed to be supported by the Analytics solution. Scholars discuss the reduced impact of Analytics if the process has a low level of uncertainty (or volatility) (Srinivasan and Swink, 2018; Zhu et al., 2018). While this takes only a certain range of application areas into account and ignores benefits for complex information inputs or benefits for faster decision-making, it presents the potential flaw of employing Analytics to processes that may offer little value in terms of return on the investment. Reversing the perspective, Oliveira et al. (2012) emphasize the need for a certain level of process maturity before employing Analytics and gaining value from it, and Srinivasan and Swink (2018) present the need for flexibility in the physical process such that reactions to analytical results can be applied. If there is no flexibility, the opportunities to gain value from Analytics are foregone since they cannot be executed. As a result, the value and benefits from Analytics depend on the status of the physical process, whose weaknesses can become barriers to utilizing the full potential of Analytics.

Assuming that all the above barriers are overcome, nevertheless the absence of governance of Analytics can hinder organizations from gaining the expected value from Analytics. A lack of top management commitment and understanding of advantages from Analytics will of course hinder the adoption of Analytics in the first place (Lai et al., 2018). When employing Analytics, the lack of governance can result in a lack of focus and missing relevance of the results produced ("measurement minutiae"), reducing the effect of Analytics (Sanders, 2016). However, scholars have stressed that the result of the absence of strategically and managerially controlled Analytics is isolated and fragmented Analytics efforts, resulting in only small benefits (even in disadvantages for other functions) and unaligned Analytics maturity along business functions (Ramanathan et al., 2017; Sanders, 2016). To conclude, Analytics efforts need to be guided by an organizational understanding of the purpose of Analytics and it should be incorporated into the business strategy. Otherwise, gaining the hoped for value and benefits can be impeded (Kache and Seuring, 2017).

6.2.3 Measures to fully utilize the benefits of Analytics

As opposed to barriers, measures are rarely addressed in the LSCM literature. Even in the field of Analytics, countering barriers is usually a side note. In particular, no study could be found systemizing measures, deriving core categories, or identifying effects and relationships. In this section, practices and measures are explored considering literature on Analytics in general and the few studies from the LSCM domain.

Schoenherr and Speier-Pero (2015) investigated several contemporary aspects related to the adoption level of Analytics in LSCM organizations and created a list of circumstances that lead to a higher motivation for organizations to adopt Analytics. Their list does not intend to show how organizations created the circumstances intentionally or unintentionally but explores the status quo in these organizations. Thus, the list does not represent executable practices. The motivators include the existence of aspects the absence of which was noted, in the discussion above, as forming a barrier, such as senior leadership promoting Analytics and displaying commitment. Further, the use of Analytics is encouraged by competitors and colleagues, and to a lesser degree by customers as well. The strongest motivator for using Analytics has been reported as the user's conviction about the value of Analytics, implying the need to experience the value from Analytics, probably in support of the user's own processes.

Scholars have presented several practices to make the use of Analytics more appealing, which could lead to increased conviction concerning the value of Analytics and motivate its continued use. This includes visually appealing software interfaces, which would also contribute to make the results easier to understand and comprehend, mobile availability via tablet computers and smartphones, which have been observed to increase the frequency of using Analytics, as well as user-engaging approaches that strive to stimulate interaction, like gamification or self-service (Wixom et al., 2013). Further, showing the outcome of decisions on individual scorecards or assessments after (minor) decisions is supposed to build trust in Analytics and show its value, while scholars report this application in a supportive way as opposed to a blaming or judging way (Ransbotham et al., 2015; Ross et al., 2013). Additionally, for stakeholders, who are needed to provide funding, Analytics can be made more appealing by articulating relevant business cases (Davenport and Harris, 2007).

In contrast, scholars have also reported more instructive practices. Recommended supportive change management efforts include promotional activities, training courses, and coaching concerning Analytics and its goals and benefits (Ross et al., 2013; Seddon et al., 2017; Watson, 2014). Further practices include underlining the necessity to discontinue non-data driven methods, the demand for data-based explanations in decision-making, and incentives for data-driven decision-making (McAfee and Brynjolfsson, 2012; Watson, 2014). One recommendation even suggests managers allowing themselves be overruled by Analytics to promote their trust in it (McAfee and Brynjolfsson, 2012). However, the replacement of employees who are unwilling to change has also been suggested (Watson, 2014).

For advancing Analytics in the organization, several practices have been presented. To create more relevant business cases requires managers to build a certain understanding of Analytics – not for application, but for understanding execution and requirements (Ransbotham et al., 2015). Another recommendation for managers is to ask second order questions, which are, roughly described, questions not about how to improve the solution to a problem, but questions around finding another solution to the problem (Marchand and Peppard, 2013). However, efforts are also suggested from the analysts' side, either by getting "translators" to explain Analytics in business terms or requiring Analytics experts to build business understanding (Bose, 2009; Davenport and Harris, 2007; Ransbotham et al., 2015). Overall, the LSCM-specific and general Analytics literature suggests an incremental and evolving approach, potentially starting in high impact areas (Bose, 2009; Sanders, 2016).

One relatively specific practice, as compared to the other practices presented above, is the collaborative approach between Analytics experts and business experts, which helps to build Analytics expertise on the business side, and vice versa, and supposedly results in better use cases and outcomes. This has been suggested by several scholars, named a "field and forum" approach, "shadowing," or simply described as the Analytics expert joining the business expert in his real-work value creation and decision-making processes, including the related data usage, to learn and discuss opportunities for improvements afterwards (Barton and Court, 2012; Marchand and Peppard, 2013; Wixom et al., 2013). Another related practice is the use of "data labs", in which experts from the different areas are co-located to work collaboratively free from the distractions of daily business (Marchand and Peppard, 2013; Wixom et al., 2013). These practices are complemented by agile development methods, in which the progress of shorter periods ("sprints") is discussed, e.g., by assessing prototypes (Wixom et al., 2013).

In contrast to these practices oriented towards individuals, some practices to align and integrate the Analytics efforts of an organization are suggested. Scholars suggest setting up an enterprise-wide information agenda and strategic directions for data and Analytics (Lavalle et al., 2011; Watson, 2014). A cross-functional integration of several business units and collaboration in the organization, e.g., in a newly created center of excellence for Analytics, and with key partners has been suggested specifically for LSCM, since Analytics initiatives quickly influence partners (Kache and Seuring, 2017; Sanders, 2016; Watson, 2014). Additionally, researchers have suggested creating a "single-source-of-truth", which demands data exchange between all business units, as an organizational measure (Ross et al., 2013), although this also touches on technological issues.

Concerning technological aspects, one issue addressed in the literature is data. Scholars have recommended creating data standards and automating data onboarding, integration, and quality processes as much as possible to accelerate the creation of insight from data (Wixom et al., 2013). It has further been observed that analytically mature organizations employ centralized groups responsible for ensuring data quality and availability (Davenport and Harris, 2007). In the context of LSCM, the structuring of data in a manner described as "scrubbing" has been recommended as a first step in maturing in Analytics (Sanders, 2016). The highlighted importance here is that the errors which would occur during data generation are eradicated such that data is already clean, structured, and organized for insight creation.

Another technological aspect comprises the IT systems. By analyzing the challenges and opportunities of Analytics in LSCM, scholars stress the status of existing IT systems and their role in making the use of Analytics challenging (Kache and Seuring, 2017). Thus, they recommend the prioritization of continuous IT investments. Concerning data integration issues in and between organizations (e.g., with supply chain partners), researchers have presented the example of digital platforms, which act as a hub-and-spoke system with interfaces to several partners and customers, instead of creating a point-to-point connection (Sanders, 2016). Such a platform would level different formats and standards.

6.3 Methodology

For this study, a mixed-methods approach has been chosen. The approach is set out in the following sections. Data collection and data analysis are explained. This section concludes with reliability considerations.

6.3.1 Research Design

A mixed-methods approach has been chosen, combining grounded theory (Strauss and Corbin, 1998) and the Q-methodology (Brown, 2004; Ellingsen et al., 2010; Valenta and Wigger, 1997) to exploit synergies between them. Explicitly, after open coding in which phenomena are identified, grounded theory intends the scholars to use axial coding to relate the identified phenomena to each other and selective coding to extract core categories (Strauss and Corbin, 1998). This search for core categories is executed via the Q-methodology, which intends to perform a perception based sorting, creating categorizations and additionally unveiling patterns of perceptions forming the categorizations and providing insights on them (Brown, 2004; Valenta and Wigger, 1997). This mixed-methods approach provides a more robust framework for the relationships compared to either individual approach. Each of the methods has been used in the context of LSCM to identify barriers and measures.

Researchers use Grounded Theory with the intention of creating deeper knowledge on a research phenomenon, and have repeatedly done so to identify barriers and measures in LSCM. For example, studies have identified and categorized barriers and coping mechanisms on implementing sustainable practices in LSCM (Rauer and Kaufmann, 2015), the implementation of supply chain technologies in emerging markets (Saldanha et al., 2015), and the transition towards a supply chain orientation (Omar et al., 2012). These studies investigated barriers to transition to a rationally more beneficial position, usually strongly influenced by human behavior, and the systematization of measures and their effects. They emphasize the capability of Grounded Theory to aggregate knowledge and build a consensus (Strauss and Corbin, 1998).

Specifically focusing on extracting consistent aggregation and groups of concepts, the Q-methodology has been used as the method of choice in LSCM research. The method has been used to form a mutually exclusive and exhaustive taxonomy of biased behavior in supplier selection (Kaufmann et al., 2010), conceptualization of moderators and sources of Supply Chain Volatility (Nitsche and Durach, 2018), and to aggregate attitudes and levels of acceptance towards different innovations and practices in low-input food supply chains across multiple cultures and multiple stages of the supply chain (Nicholas et al., 2014). These articles present, by example, the utility of the Q-Methodology for aggregating measures and extracting conceptualizations in LSCM research.

6.3.2 Data Collection

The data collection method was based on established practices. To sample relevant experts as interviewees, boundaries have to be defined (Miles et al., 2014). First, to gain a broad overview of barriers and measures in LSCM, the boundary of relevant organizations for data collection were set to include various Supply Chain actors, as introduced in Section 2.1: manufacturing (OEM and suppliers), retail, logistics service providers, and, in addition, Analytics providers with a focus on LSCM. Second, experts had to have relevant job functions related to Analytics. Third, experts had to have experience with Analytics in the context of LSCM, and thus experience with SCA. Potential interviewees were identified based on the first two criteria and invited to the study. After an invitation to participate, potential interviewees with a positive response expressing interest were sent an overview of the study (Yin, 2014). Based on the overview, the potential interviewees were asked to evaluate their experience with SCA – the third boundary criterion – and, in case of negative evaluation, asked to help to contact the most knowledgeable informants on the subject matter. If their experience satisfied the criteria, the experts were included in the study. After 12 interviews with 13 interviewees, the data collection was concluded. At this point, the identification of new barriers and measures through additional interviews had attenuated, while the effort to recruit further interviewees had increased substantially. This was evaluated as fulfilling the condition of saturation (Strauss and Corbin, 1998) and is comparable to similar studies in LSCM (Bode et al., 2014; Macdonald and Corsi, 2013; Rivera et al., 2016). Table 3 lists the interviewees.

The interviews were conducted in a semi-structured format using an interview protocol for reliability, which was initiated with a grand tour open-end question (Eisenhardt, 1989; McCracken, 1988). Interviewees were asked about barriers regarding Analytics as applied to LSCM that they were currently experiencing or had experienced in the past. Based on their responses, they were subsequently asked about two aspects: first, to provide detailed information on the barriers for increased understanding of the barriers' effect, and second, how these barriers were being/had been addressed, and how the measures used affected the barriers. Subsequently, interviewees were asked about their experience with the barriers presented in section 2.2 and, depending on the response, asked about measures taken to overcome these barriers. The second part of the interview on measures was again initiated with a grand tour open-end question on best practices used to increase the success rate of Analytics initiatives and interviewees were asked to give justifications for their use. These justifications were requested interrogated to understand whether these practices were used to solve or overcome particular problems, and whether these practices qualify as measures. The interviews were concluded with questions on the use of the measures presented in section 2.3 and, depending on the response, the justification for their use.

Participant	Position (anonymized)	Actor	Analytics exp. [yrs]
A	Manager (functional) Analytics	OEM	8
B	Data Scientist	LSP	12
C	Data Scientist	Supplier	3
D	Head of Analytics	OEM	19
E	Manager Analytics	Retail	3
F	Director Analytics	OEM	8
G	Manager Analytics	Supplier	2
H	Head of (functional) Analytics	LSP	6
I	Manager Analytics	Retail	14
J	Sen. Data Scientist	LSP	4
K	Data Scientist	Analytics Provider	3
L	Data Scientist	Analytics Provider	3
M	Head of Analytics	LSP	3

Table 3: Interview Participants

Since none of the interviewees was located near the researchers, most interviews were conducted by phone. Previous studies have used telephone interviews for interview research in LSCM as a measure to overcome the restrictions from different locations without any reported bias (Bode et al., 2014; Gligor and Autry, 2012; de Leeuw et al., 2016; Macdonald and Corsi, 2013; Manuj and Sahin, 2011; Rivera et al., 2016). Subject to the approval of the interviewees, the interviews were audio-recorded and transcribed verbatim, providing the qualitative data for analysis. The interviews lasted between 45 and 105 minutes, with an average of 65 minutes. Interviewers took handwritten notes during the interviews for the purpose of recording and guiding the interview. The Analysis was initiated after the first interviews to allow preliminary interpretations and insights, which were expanded in subsequent interviews. All data were documented in a structured database for further reliability. Audio records were deleted after transcription as committed to the interviewees.

6.3.3 Data Analysis

In the first step, the data was rigorously analyzed according to Grounded Theory guidelines (Strauss and Corbin, 1998). The analysis was initiated after the third interview to allow continuous contrasting of developing theory and data collected from the ongoing interviews (Kaufmann and Denk, 2011; Strauss and Corbin, 1998). The analysis steps, starting with open coding, were executed using ATLAS.ti (Version 8.4). During open coding, the interviews were coded to identify recurring themes. The coding was focused on identifying the underlying nature of challenging conditions during the application of SCA in the organization and extracting the actions taken to cope with those challenging conditions, their original intent, and their actual impact. Due to the intent of this research, the codes created were mainly abstractions and vivo codes of the interviewees. The interviews were continuously read and reread to establish similarities and disparities. As a result, codes and the categories they represent were restructured.

After concluding the data collection and finalizing the open coding for the data, axial coding was conducted to lift the level of abstraction as well as further restructure and aggregate existing categories (Strauss and Corbin, 1998). During this process, short descriptions of categories of barriers and measures were created as input for the Q-Methodology based selective coding process.

In this regard, the Q-methodology is used as a supplement to the selective coding steps and, thus, to the Grounded Theory approach. Scholars have emphasized the adaptability of the Q-methodology to the interest of researchers, such as using differences of sorting as input for discussions (Amin, 2000). As a result, the Q-methodology was adapted for this study to identify different patterns of thought about sorting the aggregated codes that were the output result from the axial coding step. These sorting results were used as input for consensus-building on the core categories, which the selective coding intends to derive. In this regard, participants developed their individual sorting and contributed their underlying patterns of thought to the consensus building in an unbiased manner by performing the steps of the Q-methodology and commenting on their results without the other participants criticizing the sorting. The value of the participants' comments on their sorting process has been highlighted by Ellingsen et al. (2010).

In detail, the Q-methodology starts with two steps that set up the sorting process. First, a concourse is created, which is the collection of statements pertaining to a research area of interest derived from empirical and secondary data sources (Brown, 2004; Valenta and Wigger, 1997). This step is equivalent to the open coding step that identified 154 codes – in this case on barriers in applying SCA and measures to overcome them – from the semi-structured interviews. The subsequent step is the creation of a Q-sample, which represents a comprehensive, balanced, and representative subset from the concourse (Brown, 2004; Valenta and Wigger, 1997). This step is intended to limit the number of statements by grouping similar statements and refining statements that are too specific or too general (Ellingsen et al., 2010; Valenta and Wigger, 1997). This step is equivalent to the axial coding step that related similar codes in the data, 30 barriers and 59 measures.

The sorting procedure, named Q-sort, is performed on the Q-sample as a third step (Ellingsen et al., 2010). As participants, three researchers with high expertise on LSCM with different viewpoints on Analytics have been chosen. In accordance to Ellingsen et al. (2010), the participants received a sorting instruction, were reminded about the non-existence of a "right" sorting, and were given the task to perform the Q-sample freely. The sorting instruction was explained as to sort the items based on the participant's perception of similarity. The free mode of the Q-sort was chosen such that the participants had to create their own groups. This approach intended to promote the strength of the Q-methodology, as repeatedly emphasized, of uncovering different patterns of thought, perception, and opinions, which can be used to asses areas of consensus and friction (Amin, 2000; Brown, 2004; Valenta and Wigger, 1997). Here, consensus on the core categories of barriers to SCA and measures to overcome these barriers was assessed.

6.3.4 Reliability

The reliability of this study was judged based on criteria regularly used by scholars evaluating the reliability of similar studies (Flint et al., 2002; Omar et al., 2012; Rauer and Kaufmann, 2015; Thornton et al., 2013). The criteria of credibility, transferability, dependability, confirmability, and integrity in these studies emerged from the recommendations of Hirschmann (1986) as well as Lincoln and Guba (1985). The criteria of fit, understanding, generality, and control emerged from Strauss and Corbin (1998).

Credibility describes the extent to which the results are acceptable representations of the data. It was addressed by the timeframe of four months in which the interviews were conducted, the review of the research summary by the interviewees, and the Q-methodology that led to a review of the codes by three researchers (Flint et al., 2002; Omar et al., 2012; Thornton et al., 2013).

The extent to which the findings can be applied from one context to another is covered in the criterion of transferability. This was addressed by the theoretical sampling, which led to a diverse set of organizations, business sizes, and roles in the supply chain (Flint et al., 2002; Omar et al., 2012; Thornton et al., 2013).

The criterion of dependability refers to the dependence of the results on time and place, and as a result the extent of the results' stability and consistency. To ensure dependability, interviewees were asked to reflect on the decisions, actions, and changes over time that were related to the phenomenon and, thus, their past and present experience (Flint et al., 2002; Omar et al., 2012; Thornton et al., 2013).

Confirmability measures the extent to which interpretations are the result of interviewees' experience as opposed to researcher bias. To create confirmability, the research protocol was used before and during the interviews to ensure that interviewees could prepare and answer without researcher bias (Eisenhardt, 1989; Yin, 2014) as well as by providing the results to the interviewees for review (Flint et al., 2002; Omar et al., 2012; Thornton et al., 2013).

Integrity of this study, representing the extent of influence by misinformation and evasion by participants, was ensured by conducting non-threatening, professional, and confidential interviews (Flint et al., 2002; Omar et al., 2012).

The extent to which the findings were a fit to the area under investigation, inherent in the criteria of fit, was addressed by the credibility, dependability, and confirmability criteria (Flint et al., 2002; Omar et al., 2012).

The results' reflection of the "own world of the interviewees, which is covered in the criterion of understanding, was addressed by providing the results to the interviewees with a request for comment and review (Flint et al., 2002; Rauer and Kaufmann, 2015; Strauss and Corbin, 1998).

Generality describes the extent to which the findings discover multiple aspects of the phenomenon under investigation. It was addressed by applying the Q-methodology to integrate different patterns of thought into the study (Valenta and Wigger, 1997) and by conducting interviews of a sufficient length (45–105 min), with extensive openness by the interviewees, strongly focused on the area under investigation and covering multiple facets related to that area (Flint et al., 2002; Omar et al., 2012; Rauer and Kaufmann, 2015; Strauss and Corbin, 1998).

Finally, control describes the extent to which organizations can influence aspects of the emerging theory. By focusing on measures, the study strongly focuses on aspects over which organizations have control, which was discussed with the interviewees during the study to establish the existence of control (Flint et al., 2002; Rauer and Kaufmann, 2015; Strauss and Corbin, 1998).

6.4 Results and Discussion

Resulting from the analysis of the data, one framework regarding the impact of barriers on SCA initiatives and another framework regarding the measures to counter these barriers have been derived. Due to the analysis, core categories have been extracted and abstracted, which assemble the frameworks. This section presents and explains the derived frameworks.

A major inference made from the analysis of the collected evidence has been that barriers and measures affect different steps along the cycle of applying Analytics to a LSCM organization. During the Q-Methodology, the researchers built consensus on distinguishing four phases:

(1) "Orientation about Analytics" describes actions, circumstances, and events before specific Analytics initiatives are planned. During the orientation, the necessary conditions for applying Analytics are created and employees are motivated to invent Analytics initiatives to be executed.

(2) "Planning of Analytics initiative" describes actions, circumstances, and events during the set-up of a specific Analytics initiative, in which the addressed business problem/ business case is specified, the approach designed, resources and budget committed, and relevant people are invited to participate.

(3) "Execution of Analytics initiative" describes actions, circumstances, and events during the development and creation of Analytics solutions in specific Analytics initiatives. For example, this includes interactions with data, applications of

analytical methods, the use of technology, and interaction of analysts with business experts.

(4) “Use of Analytics solution” refers to actions, circumstances, and events after the solution development, which include the deployment of the Analytics solution to users and their interaction with the solution in the short and long term.

Allocating the effects to project models such as CRISP-DM was rejected as unsuitable. Several barriers and measures occur outside the usual scope of such models. Further, barriers and measures show similar effects in most solution development phases, which are differentiated in too much detail in these project models.

In addition, as extracted from the evidence, a distinction in the impact of barriers and measures is made into capabilities and culture. Capabilities refers to the capabilities of the organizations, the organizations’ processual and technological infrastructure and standards, as well as the knowledge and skills of organizational members. On the other hand, culture in the context of this study refers to the attitudes and behaviors of single individuals or groups of individuals in the organization, such as their motivation, solution-orientation, feelings, openness, and willingness, as well as their critical reflection on their attitude and behavior. In this sense, culture does not have to reflect the general culture of the organization, but only groups of individuals of the organization.

6.4.1 Barriers

Barriers that occur while applying SCA can be allocated with high confidence to either capability issues or cultural issues. Ambiguous cases, which researchers had to discuss extensively, were solely found in actors who omitted critical reflection on their decisions, creating problems in subsequent process steps. Eventually, a consensus was reached about such behavior corresponding to the attitudes of the actors and has, thus, been allocated to the cultural side. Below, the identified categories of barriers and their impacts are described, with examples. The framework of barriers on applying Analytics to LSCM is presented in Figure 26.

From an aggregated point of view, the evidence shows that cultural barriers occur more frequently during the phase of orientation and use, whereas capability barriers are more frequent during the phases of planning and execution of Analytics initiatives. This result is not surprising, since the phases of orientation and use demand the engagement and motivation of, as well as interactions among, individuals who have their primary focus

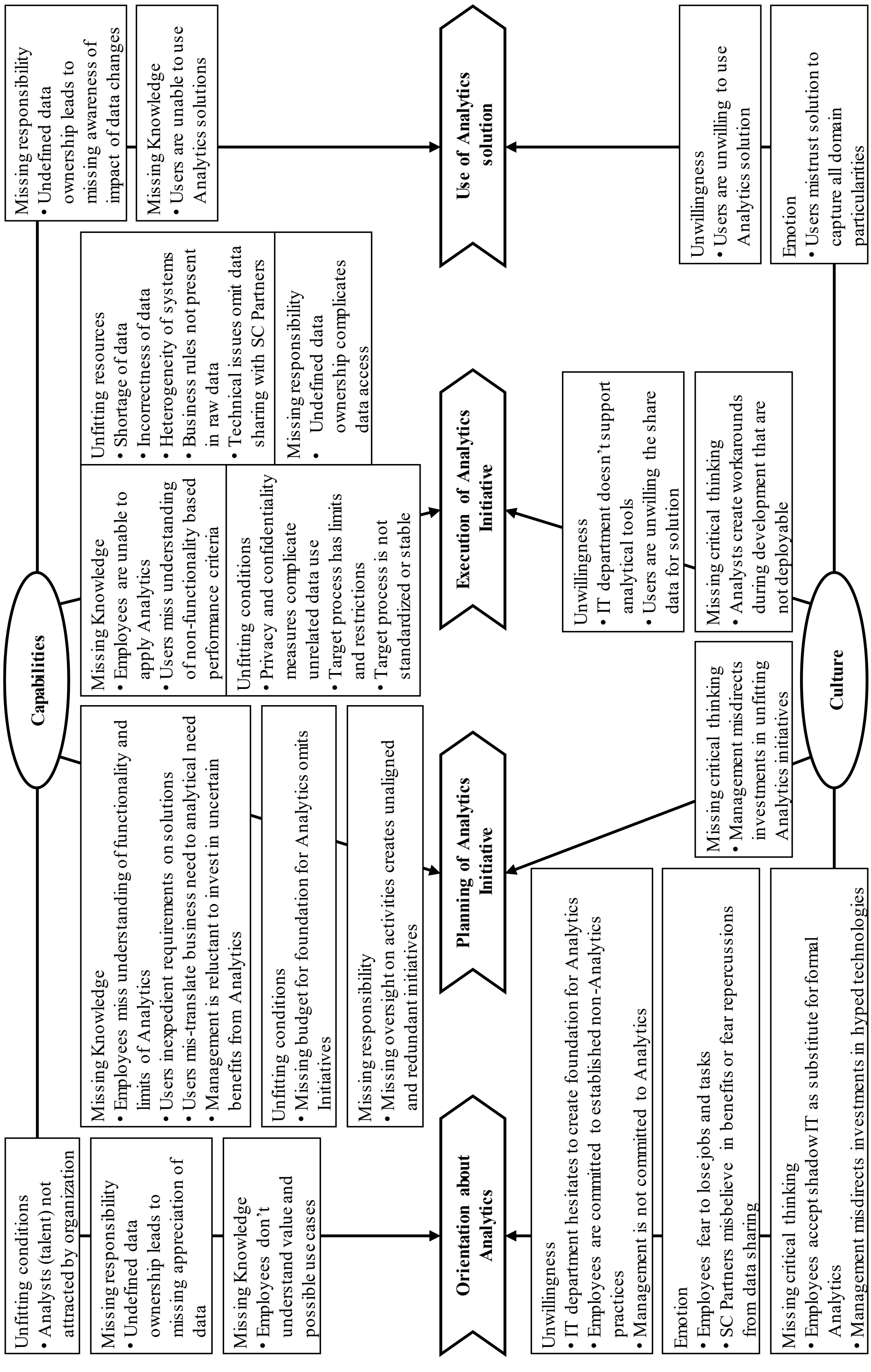

Figure 26: Barriers of Supply Chain Analytics

on tasks and activities unrelated to Analytics. Unfamiliarity with and distance from the topic create a different attitude and behavior towards Analytics as opposed to that of analysts. Interviewees repeatedly emphasized that this unfamiliarity and distance must be overcome by clearly showing these individuals the benefits of Analytics in their specific areas of work. Capability barriers in these phases can either not be determined specifically, since the specific problem for an Analytics initiative is not determined in the orientation phase, or the potential capability barriers were addressed in the solution development prior to use. The other way around, in planning and execution individuals familiar with and close to Analytics are necessary, resulting in reduced barriers of attitude or behavior in terms of unwillingness. However, discrepancies between needed and available skills, technology, and data are impactful since they hinder the tasks and activities necessary for solution development.

6.4.1.1 Capability Barriers due to unfitting conditions

Barriers due to unfitting conditions refer to circumstances in the organization's processes, infrastructure, environment, or reputation that strongly impede or prevent the execution or completion of the development of an Analytics solution. The results show that such barriers have been observed in all phases except for the use phase. An early obstacle for organizations is absence of the talent needed for Analytics initiatives. Such talent does not perceive LSCM as an attractive or challenging domain, as opposed to technology organizations at the methodological forefront. In the planning of initiatives, efforts can be halted due to various missing tools, technologies, or data needed for the initiative. These foundational conditions can be missing since organizations – especially smaller organizations – lack the budget for continuous investment. Further, such conditions can become apparent during the execution of the initiative, when activities have already begun. An example is the realization that the target process cannot be supported by Analytics as intended, either because it is not standardized and stable enough to create a beneficial solution or because it has process limits and restrictions that prohibit creating improved solutions compared to those that exist. Such conditions usually demand fundamental changes in the organization outside the realm of Analytics.

6.4.1.2 Capability Barriers due to missing responsibility

Barriers due to missing responsibility occur along all phases and usually result in extra effort, avoidable with clearly assigned responsibilities. Missing responsibility on ownership of data sources and the necessary actions and requirements connected to these responsibilities leads to situations in which knowledge about existing data sources and their location is unevenly distributed and the data and their flow are not well documented. Thus, individuals in the organization lack the understanding of data and their importance – an important component for the invention of potential initiatives. In specific initiatives, this complicates execution due to unnecessary effort to access data owners and their data, effortful coordination between several owners, and missing traceability of data usage through the organization. Imprecise responsibilities on data may result in changes to data by employees unaware of their relevance to Analytics solutions in use, compromising the solution without any communication of changes. In addition, missing oversight of Analytics leads to the development of heterogenous tools, methods, and solution approaches, likely to produce redundant solutions for similar problems.

6.4.1.3 Capability Barriers due to missing knowledge

Missing knowledge on Analytics is a substantial barrier to using Analytics and can affect the application of Analytics in LSCM organizations in a variety of ways. Without individuals in business processes who understand Analytics and have experienced how Analytics can create value, the search for potential initiatives in an orientation phase is less likely to result in meaningful initiatives for these business processes. Since the value is usually generated indirectly from actions taken due to the Analytics solution, this barrier is inherent regarding Analytics. During the planning phase, this indirect value generation and also the inherent uncertainty of the generated benefits, which are highly dependent on the data and context, can lead to underestimation of the resulting value and reluctance towards investments. The other way around, missing knowledge can result in high and unworkable expectations, impractical or absurd demands on solutions abilities, and ignorance of the limitations of Analytics. Combining this with a missing ability to translate the business need into an analytical need due to missing knowledge, these Barriers will result in initiatives that have no way of achieving the unrealistic or mis-communicated objectives. In the execution, missing knowledge on functionality of Analytics can result in the inability to let the business experts participate in the solution process, or missing understanding of performance evaluation in Analytics can result in the inability to gain acceptance for progress. Lastly, missing knowledge can result in the users' inability to use the developed Analytics solutions in their business processes, denying the actual gain from the solution's value.

6.4.1.4 Capability Barriers due to unfitting resources

Unfitting resources (data and systems) are barriers that become present during the planning or execution of Analytics initiatives, but usually affect the execution. Unfitting resources can prolong the development of the solutions, yield subpar success, or even halt the solution. These issues are usually technical, such as the relevant data is missing, especially for machine learning or time series methods; the data is incorrect, requiring intensive cleaning and feedback for correct values from the process experts; or the accessible data does not fully reflect the business rules, requiring additional preparation. While solving these issues is foremost time intensive but solvable upon identification, the identification of incorrectness or lack of fit to business rules might occur at a late stage, such that the effort is doubled, or the solution developed from the data does not gain acknowledgement from the users. Further, technical issues related to heterogeneity of systems and the resulting incompatibility of the data with the systems prevent data access or the integration of the data for more comprehensive analysis, which can either be overcome with additional time and effort, or development of the solution may ultimately be abandoned.

6.4.1.5 Culture Barriers due to unwillingness

As mentioned above, the reference to culture considered in this article does not have to reflect the culture of the general organization, but can apply to small groups of individuals. In this case, small groups that behave unwillingly in their areas of responsibility can seriously impact the success of Analytics in an organization, including specific initiatives or the ability to perform Analytics at all. Considering the barriers of unwillingness, they become relevant when individuals motivated for Analytics become dependent on the input and cooperation of others. During orientation, the dependency on IT departments to create the foundation for Analytics in data and analytical software can block the efforts of motivated individuals, when the IT department is unwilling. Interdependent with this, employees unwilling to commit to Analytics will suppress management's motivation for Analytics, while missing commitment from management can suppress employees' motivation (and necessary resources such as budget) for it. During the planning phase, when ideas are expressed, the motivated individuals bring together their ideas and business problems but are less dependent on third parties, assuming this phase is entered after management expressed support. In the subsequent phases, in particular the unwillingness of potential users to provide their data or to use the solution can have a strong negative effect on the benefits realized with deployment of the Analytics initiative. This unwillingness can be traced to an unwillingness to change any business customs that are already established, because of the effort to change (or rather the ease to remain with the familiar) and the implication of changes, such as different responsibilities (including reduced control), modified behavior, and altered processes. This is often accompanied by an expressed disbelief in the potential and value of anything that is not the habit.

6.4.1.6 Culture Barriers due to emotion

Emotions, especially of fear and perceived unfair treatment, are strong barriers to employees accepting the organization’s pursuit of Analytics or use of solutions. In the data, they have been primarily observed as a reaction to information asymmetries of individuals not actively working on Analytics or not involved in solution processes, who fill the asymmetries with assumptions. Involving employees such as potential users or supply chain partners in the planning and collaborating with them in the execution can create some level of transparency, such that emotion is a lesser barrier in these phases. However, in the phase of orientation, during which employees and supply chain partners might be left without well communicated intentions of the usefulness of Analytics or might not fully believe the communicated intentions due to events in the past (e.g., something that builds general mistrust unrelated to the individuals eager to use Analytics), they might react emotionally to the information asymmetries. In detail, employees fear losing their jobs and supply chain partners fear repercussions from sharing data, building resistance against Analytics initiatives. Similarly, developing solutions such that the solution process is not transparent to the potential user can lead to mistrust and skepticism towards the solution by the users. This emotion of mistrust is a reaction to the information asymmetries between requirements and the adherence to the requirements by the developed solution. This is particularly nurtured by analysts who over-sell their solutions.

6.4.1.7 Culture Barriers due to missing critical thinking

Missing critical thinking in the context of this paper refers to decisions made without the necessary reflection of these decisions. While this could be a result of missing knowledge and, thus, be a capability barrier, it can also result from not taking enough time and effort for consideration, or enthusiasm about a critical problem finally being solved, which is not to be impaired by critical considerations. This can occur as bandwagon behavior from management directing the budget towards some hyped technology or some hyped use cases unfitting to the business need, while the budget would be needed for foundational technologies or uses cases that are boring, but beneficial. The missing business impact of hyped but failed initiatives can generate mistrust of employees in new technologies, as discussed above. On a user level, the continued use of business owned tools/shadow IT, which usually lack adherence to standards, documentation, or may even have errors, is often not critically reflected on regarding the impact of the creator leaving the organization, compatibility with other systems, or fit with business strategy and rules. Thus, the development of a standardized and adhering substitute in an Analytics initiative is usually not triggered, while being highly necessary. During solution development, one recurring issue is the creation of workarounds – technical debt – by analysts without reflection on the impact on later development stages. The issues usually surface later and create additional effort or can even prevent the success of the Analytics solution and its benefits.

6.4.2 Measures

Overall, an allocation of measures that are directly assigned to specific barriers could not be derived from the data, since interviewees expressed that some measures address several barriers, and vice versa, by intention or not. Further, interviewees explained that measures are adjusted and advanced over time as a reaction to the specific needs and capabilities of the of organization and employees. Thus, measures on barriers are path and context dependent. While several measures are presented in the following section, it must be emphasized that the presentation is reduced to core categories as derived from the grounded theory process. Examples are presented to improve comprehensibility and to further illustrate the core categories. It cannot be generalized that certain, specific measures will help all organizations to overcome certain, specific barriers, especially in their vanilla form.

Reduced to the core categories, measures generally address capability barriers but contribute to overcoming cultural barriers at the same time. Acceptance is gained by building knowledge and creating processes for more transparent development and information exchange – information asymmetries are reduced. Thus, the cause is addressed (missing capabilities), but not the symptoms (unwillingness). Comparably to the barriers, the identified measures affect the different stages of the Analytics initiative lifecycle differently. While demystification is essential to aid the orientation phase, the

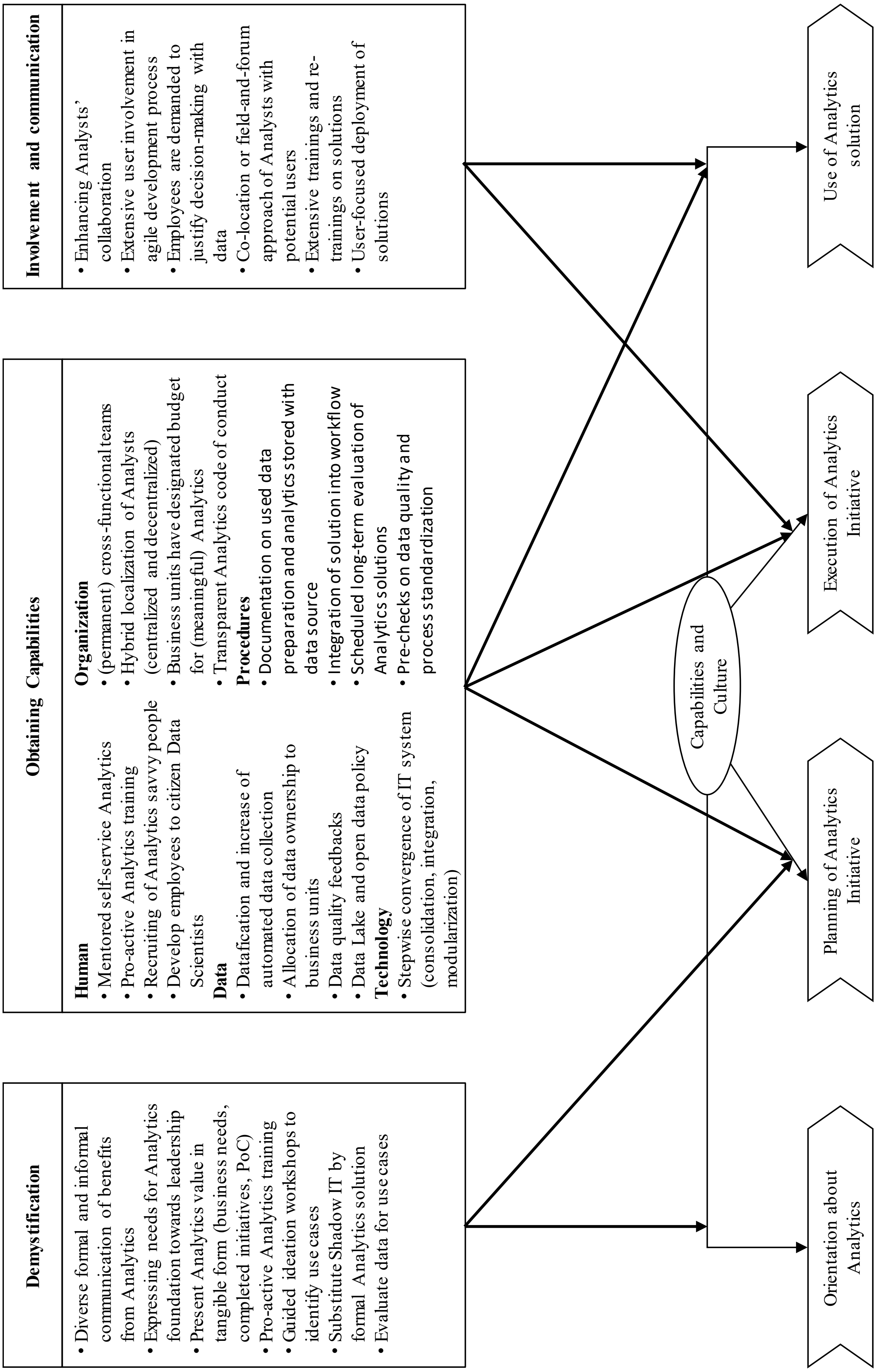

Figure 27: Measures to support Supply Chain Analytics

creation of specific capabilities affects the project development phases and communication and involvement become vital for the actual analytical work in the execution and use phases. The links are illustrated in Figure 27, with examples for measures in the respective core categories.

6.4.2.1 Measures contributing to demystification

The measures contributing to demystification are intended to communicate the value and benefits of Analytics, fitted to the intended receivers and their context. The most widely used measures to reach the mass of employees are formal and informal communications presenting achieved value and benefits, such as workshops, presentations, internal conferences, or communication material. Showing achieved value, especially accompanied by individuals who benefitted from the executed initiatives, was explained by interviewees to be effectively convincing and to give the opportunity to address questions and lack of clarity in live formats. However, critics may not attend and, thus, may not be convinced. Successful initiatives are therefore to go on tour with roadshows disseminating the evident benefits of Analytics across the organization. Similarly, pro-active trainings on Analytics create an understanding of it and allow answering questions. Even applied to employees less likely to use the methods, this resource intense approach creates acceptance and a realistic expectation. Another form of demystification is the creation of use cases combined with process experts for their respective domains (e.g., the different units involved in the LSCM activities). The created use cases represent a more tangible and, thus, comprehensible form of value from Analytics. Similarly, this approach is more likely to convince supply chain partners to cooperate. Use cases can be identified by guided ideation workshops, evaluating existing data sources, as part of pro-active training, or by offering to formalize business owned tools/shadow IT. To demystify Analytics for top management, time for conferences and training events is rarely available. Investments are motivated by the value from tangible and clear use cases, or a consistently voiced need for investments harmonized across several business units.

While the value created by Analytics initiatives is mostly uncertain, different approaches for a value estimation exist. Estimations based on comparable solutions (e.g., other organizations or business units, previous initiatives) or based on the terminated inefficiencies engaged in the Analytics initiative are preferable, but such tangibles are frequently missing. Thus, the creation of proofs-of-concept or prototypes is needed, which demands initial investment to allow a value estimation. If these initial investments are too high (i.e., cost intense data collection), a rare approach is the use of hypothetical prototypes, for which the data are simulated. However, this kind of prototype only tests ideas and requires serious changes to develop a production-ready solution.

6.4.2.2 Measures contributing to obtaining capabilities – Human

Enabling humans by building their Analytics capabilities involves several forms of training, dependent on whether they are expected to contribute to Analytics initiatives as domain experts or expected to apply analytical methods. To enable their contribution, either a training event for employees is carried out, or data savviness becomes a recruitment criterion for business roles and top management. The approach of enabling contribution accepts that not every employee needs to execute analytical methods. However, this portion will decline, while not every employee can be upskilled. To improve application capabilities, self-service Analytics and Citizen Data Scientists are created. In self-service Analytics, employees are provided with role specific tools which allow data-driven decision-making and dedicated analytical analysis for their roles. This should be fed back by analysts regularly. The Citizen Data Science concept acknowledges that certain employees are already practically in the role of an analyst for their respective unit. These are identified, provided with additional training and the respective title to act as analyst in the business while having strong domain knowledge, therefore providing the first contact for analytical inquiries. Both concepts improve access to Analytics to allow employees – potential users of Analytics solutions – easier interaction with Analytics.

To get access to analytical talent, organizations may alter their image to appeal to potential candidates outside of the company. This includes the portrayal of analytically complex and innovative initiatives and the active engagement of the talent in universities and platforms relevant for that talent (conventions, internet forums). As talent is understood to be a limited resource necessary for superior performance in competition, organizations must take active steps to attract that talent.

6.4.2.3 Measures contributing to obtaining capabilities – Data

In regard to data being repeatedly expressed as an inevitable issue in any Analytics initiative in the discussions on barriers, the multitude of described measures was not surprising. However, these measures are often peripheral topics to other core categories. Considering the measures solely dedicated to data, centralizing data and establishing open data policies are supposed to create access to the data needed for individual analysis and Analytics initiatives. Further, measures to design data collection processes such that the eventual collection of sensitive personal data is factored in beforehand reduce side effects on accessibility of related non-sensitive data. Emphasized for data quality and availability are automation, such as automated data collection, validation rules for manual data collection or the automated interpretation of free text with machine learning, as well as increasing datafication of processes and products, in consultation with analysts. In conclusion, the measures emphasize the design of data collection and storage under the consideration of future use of the data for Analytics.

Measures peripheral to organizational measures include organizational measures to improve data quality and availability. The core of the collected measures is to create awareness on data quality at the point of data creation, which is the business unit. This includes the allocation of data ownership and responsibility to the business units, providing feedback and training on data quality, but also, in return, establishing data quality business units as points of contact for issues and guidance. Peripheral measures with technology will be discussed below.

6.4.2.4 Measures contributing to obtaining capabilities – Technology

The capability building measures for technology address the creation of an IT ecosystem that supports Analytics. This means, on the one hand, creating accessibility and consistency of data, and on the other, to enrich options for Analytics solutions and enhance the deployment of solutions. The essence of technology capability measures taken by organizations is to develop the IT ecosystem towards a single-source-of-truth. However, this vision might not be achieved – or even aspired to – since it displays a level of complexity that is hard to handle and might not be cost efficient. In particular, the idea of leapfrogging to this vision was explained by interviewees to be unreasonable. Instead, organizations move in the direction of this vision in different forms dependent on their individual needs either by consolidating IT Systems in smaller numbers and integrating obsolete systems into newer systems; by setting up IT platforms as integration layers, which allow interchange between systems; or by replacing systems with more modular systems to develop a plug-and-play style IT ecosystem. Thereby, the platform solution is the preferred way to overcome technical integration issues with supply chain partners. In conclusion, the measures taken that aimed to create IT ecosystems for Analytics need a few years' foresight to keep complexity controllable and investments reasonable.

6.4.2.5 Measures contributing to obtaining capabilities – Organization

To clarify, organizational capabilities address changes of the organizational structures and processes, while procedural capabilities address changes of the analytical solution development process. The organizational capabilities have several focus areas, including structures that reduce the organizational distance between analysts and domains, as well as creating a better understanding of each other's tasks and issues. This includes the localization of analysts in a hybrid format with centralized analysts in a center of excellence and decentralized analysts in the business units to exploit the advantages of both forms. Dependent on the existing structures, a recurring measure is to enhance process improvement units with Analytics to make use of the existing closeness of these established units and the business domains. Further, the initiatives are executed in cross-functional teams. One organization advanced the latter to permanent cross-functional Analytics teams with own backlog of projects.

Another focus area is the development of, and commitment to, rules and codes of conduct. This can be employee focused to build acceptance and trust in Analytics, such as a code of conduct on what restrictions exist on accessing and analyzing data as well as committing to restrictions for automation solutions, which must benefit the employees instead of replacing them. Transparency and communication of these commitments are key. The rules can further be organization focused and shift control on Analytics related decisions. Examples are the centralization of decisions on sharing data with partners or even making data sharing part of contracts with partners, which is becoming more frequent due to service level agreements and performance evaluations.

Finally, designated budgets for Analytics as an organizational change in the budgeting process are used to stimulate Analytics Initiatives. However, the appropriateness of the resulting initiatives needs to be checked (e.g., by consultation with analysts).

6.4.2.6 Measures contributing to obtaining capabilities – Procedures

The collected measures to enhance the development process of Analytics solutions are most notable for presenting reactions to overcome issues. Some of these formalized procedures address information and knowledge gaps, which are time- and resource-consuming to close, while the measures are merely cost-efficient fixes. As described by the interviewees, the solution for these gaps is to gain experience with Analytics, which can be achieved by participating in Analytics initiatives where the fixes are used to ensure avoiding these issues until the experience gained makes them obsolete. In this sense, business experts' inability to translate business needs to analytical needs can be fixed through review and feedback with analysts. Analysts' misinterpretation of users' demands for Analytics solutions, which are as a result unneeded and unused, is fixed by formal agreements establishing commitment and willingness. Business experts' unwillingness to cooperate is fixed by analysts assuming responsibility for the focal decision-making processes of the Analytics initiative. Other formalized measures schedule activities early to avoid impairing issues in later stages. This can occur during the stage of project execution, supported by pre-checks of available data, or process stability and flexibility, and cloud-hosted containerization of the solution development. This can also occur during the phase of using the solutions and facilitating their long-term success using documentation, including incorporating solutions into standard operational procedures and scheduling long-tern evaluations of the solutions as part of deployment.

As pointed out by one researcher during the data analysis phase of this article, some measures listed under this core category are merely practices for successful project management. However, humans might have difficulties in transferring practices from one domain of application to another while still collecting experience with the new domain.

6.4.2.7 Measures contributing to involvement and communication

The final core category of measures identified represents measures contributing to the creation of involvement and communication in order to improve each side's understanding of the other side's actions and needs, to improve decision-making. These measures can benefit an executed Analytics initiative both directly and indirectly. Direct measures address a high level of involvement of the intended users in the development process, such as early and constant inclusion in an agile solution development format with regular sprint meetings, co-location of analysts and users, or a collaborative field and forum approach with analysts directly observing and taking part in the activities and decision-making of the users. Further, deployment processes can focus extensively on the users' experience with the solution by presenting the solution in a user-oriented form, by gradually introducing the solution into the process, or by providing consumable and user-oriented training events. Interviewees emphasized that the focus on the user during all stages of development is vital for the initiative's success. Besides the importance of user involvement, it was further acknowledged that the user's mindset is occupied with their business responsibility, while their obligation to an Analytics initiative is the advocation of business interests and not the understanding of analytical methods.

However, to advance in Analytics, the organization's employees need to develop an understanding of the interpretation of the results of Analytics solutions and their implications, and become familiar with this. Thus, a repeatedly highlighted indirect measure is constantly requesting justification for employees' decisions in the form of data-based results. Another indirect measure is to promote and support exchange of analysts. These indirect measures create an environment that enhances collaboration in potential upcoming Analytics initiatives.

6.4.3 Discussion on applying measures and handling barriers

As introduced above, the impact of measures on an organization could not be generalized from the data and is highly dependent on the context of the organization. Due to this and the dynamic nature of measures existing at different stages of development, allocating measures to specific barriers was not supported by the collected data. Below, further points regarding the core categories derived from the Grounded Theory methodology are discussed.

Considering the capability barriers, the variety of requirements for more complex Analytics initiatives are underlined. Scholars have highlighted the need for a technical foundation (Lavalle et al., 2011) as well as the required talent (Sanders, 2016), the co-dependency on technical capacity and skills (Kiron et al., 2014), the need for data quality (Hazen et al., 2014), or the required knowledge of employees and managers (Manyika et al., 2011). This study identified a multitude of requirements: analytical talent, the IT systems landscape, the data to be analyzed, organizational structures, the knowledge of the people expected to cooperate with analysts, and the condition of the unit of analysis. Thereby, this study identified that data interacts with all other requirement, while decreasing in quality and accessibility subject to these other requirements. In particular, lack of responsibility affects data negatively, which indicates a missing understanding of data as an organizational asset – a paradigm scholars have emphasized in the past (Kiron et al., 2014). However, interviewees reported impactful results achieved with analysis on a small scale – small enough to be run on personal laptops – demanding lower levels of commitment.

Discussing cultural barriers, this study uses this label for the behaviors and beliefs of individuals in the organization, which may not reflect the general culture of the organization. The barriers allocated to this category highlight the cross-functional nature of Analytics in LSCM, since they result from treating Analytics as an isolated technology topic. The need for collaboration and exchange has been discussed in the literature (Janssen et al., 2017), but this study emphasizes the information asymmetries resulting from lack of cooperation as having the consequence of individual beliefs that negatively impact the acceptance of Analytics in the organization. While unwillingness on the employee level is the more direct effect to observe, this study coincides with Hayes's (2018) argument that unrealistic expectations and visions have negative effects as well. These are different individual beliefs of overestimation resulting from information asymmetries. However, relating to literature and interviews, this issue is not Analytics specific, but an issue of change management and human resistance to change, as observed with many technologies.

Concerning measures, the concept of demystification was of notable importance to the interviewees as part of their work. Scholars have addressed convincing employees and management, and, to enable employees to experience the value from Analytics (Schoenherr and Speier-Pero, 2015), recommend starting with smaller initiatives to obtain presentable successes (Lavalle et al., 2011) and discuss other measures to show the benefit of a data-driven organization as examined in the theoretical background. However, this study has identified a multitude of additional approaches to achieve this, which are used in parallel, displaying the practical relevance of this core category of measures. Their intent is to close the information asymmetries and set realistic expectations while building on objective and presentable benefits. At best, the cases presented are as close as possible to the tasks and processes of the individuals to be convinced. Neither is there indoctrination involved, nor an insistence on believing the benefits without evidence.

The notion of a "data-driven organization" to address human capability is broadly present in the literature (Barton and Court, 2012; Holsapple et al., 2014; Ross et al., 2013). This study underlines that this idea requires employees who are able to include data in their decision-making process instead of an organization composed only of analysts. Analysts are complementary to the organization's roles, not substituting. Moreover, interviews underlined that organizations already have analytics-savvy people amongst their employees – the topic has grown on organizations and did not appear spontaneously, as the rise of interest in recent years might suggest. These employees need to be used intelligently and have their skills uplifted. However, external talent can provide external stimulation and access to the latest methods, although attracting them might be cumbersome. But a growing supply of talent and the increased use of existing resources result in a decrease of scarcity and its estimated impact (Manyika et al., 2011).

Concerning the creation of data capabilities, this study has repeatedly emphasized the non-technical measures that need to be taken. Besides that, an extraordinary point raised in one interview is the reusage of unstructured data in free text fields, because the usual approach of dismissing the data and replacing the collection with selectable options was not possible. While data quality is an issue and there are obvious data collection errors (Hazen et al., 2014), free text data collection might be beneficial for a variety of reasons. Hence, the collection approach should be selected in accordance with the information needs of the organization and not solely with the analytical methods it is intended to apply. Additionally, while analysts must cooperate with the users, for new product developments whose benefits to the organization are intended to be analyzed only after release, the analysts assume the user role and the scenario turns around. The user-orientation applies vice-versa in this situation and analysts need to be involved in new product development.

Measures for building technology capabilities were not found to be a regular focus of Analytics literature. Platform concepts or general investments in IT have been suggested (Kache and Seuring, 2017; Sanders, 2016), while the technology measures collected in this study show a certain modesty. The single-source-of-truth is a vision to converge to, but leapfrogging is not considered as necessary due to its complexity for most LSCM organizations. First, established organizations experience a high heterogeneity of IT systems, which is challenging to integrate into one in a single action. Second, the resulting IT system will likely be challenging to manage. For this reason, even digital business models, which have an advantage in this area, must decide how much single-source-of-truth they can afford to out-benefit the effort to keep the system running. Concerning the modesty mentioned above, interviewees explained they currently have enough use cases, and therefore do not require single-source-of-truth right away. They can keep themselves busy, gain benefits from Analytics, and transform their organizations to data-driven ones while the IT systems converge to a single-source-of-truth in stages.

The measures to build organizational capabilities intend to reduce the organizational distance between Analytics and business process experts. Reducing distance has been discussed previously, with beneficial measures such as a hybrid model of centralized and decentralized localization of Analysts (Díaz et al., 2018; Grossman and Siegel, 2014), or the implementation of data governance (Kiron et al., 2014; Ransbotham et al., 2016). Beyond that, this study has presented further benefits of such measures. For example, accessibility of Analytics to employees is created, the creation of oversight on Analytics and exploitation of synergies from similar use cases is enabled, and trust in the analytical activities and the handling of data is built. Further, this study emphasizes the need for a user that utilizes an Analytics initiative's solution in a way that the value and benefit of that initiative is realized. In order to achieve this, measures must be taken such that the users – the employees intended to use the developed solution – contribute their requirements from the solution to the development process. In addition, for strategic purposes in LSCM organizations, Analytics was emphasized as supporting the organizational strategy, not being it. Analytics capabilities should not be developed for the sole purpose of developing them.

The measures to create procedural capabilities represent project management experiences with Analytics. As reported in the literature, Analytics is approached along different paths by different organizations (Kiron et al., 2012) – or rather, the path is not clear in the beginning and organizations have to test what is best for them. Above, some measures were discussed as good project management practices detached from Analytics. However, an organization coping with the complexity of larger Analytics initiatives with low experience might be distracted from applying their known good practices immediately and therefore make fundamental project management mistakes. Hence, the literature has recommended implementing Analytics technical policy committees that collect good practices and set standards (Grossman and Siegel, 2014). Further, distributing the practices amongst analysts requires coaching, since they might be unaware of the hazards of certain practices (Harris and Craig, 2011). Thus, practices may evolve as a reaction to issues, because it takes time to recognize issues as such. Due to this evolving character and, if existent, such collection likely to be considered as intellectual property not to be shared in interviews, additional practices relevant for this category may as a result not have been collected.

The vitality of presenting a product in such a way that the intended users have the most comprehension of the product's benefits and features is not surprising, therefore the measures contributing to involvement and communication are not particularly innovative. Nor is it surprising that frequent involvement of users in the development process results in improved adherence to needs and requirements. However, the measures in this category are mostly of such a type, but were explained as the results of gaining experience with Analytics. The literature occasionally illustrates an outdated picture of "back office" analysts with few user interactions (Davenport and Harris, 2007). For such analysts, adopting collaborative approaches has been an effortful learning process. Transferring these approaches to Analytics improves mutual understanding of users' domain requirements and analysts' analytical requirements (Waller and Fawcett, 2013). Several measures building on these approaches have been presented, including, but not limited to, recommendations in the literature, such as visually appealing solutions and translation of solutions into business terms (Bose, 2009; Wixom et al., 2013). In addition, indirect measures of collaboration were presented, which are not part of the solution development process and may at first appear annoying or distracting, but can provide benefits later on.

6.5 Conclusion

This study investigated barriers of implementing and successfully applying Analytics in LSCM – Supply Chain Analytics – and measures to overcome barriers. The primary focus was to identify measures to provide managers in LSCM organizations interested in using Analytics with indications of barriers to pay attention to and avoid as well as to provide them with measures to improve their actions and Analytics initiatives including the data-driven decision-making nature of their employees. As a result, this study has pursued an exploratory objective. The secondary focus of this study is the systematization and extraction of core categories from the identified barriers and measures. In regard to the systematization of conceptual contributions by MacInnis (2011), this research is "delineating", with the researchers taking the metaphorical role of cartographers, mapping the entities and their relationships. To achieve this objective, this study used the Grounded Theory approach supplemented with the Q-Methodology.

The results of this study in this regard are as follows. Barriers of SCA have been mapped into two core categories: capabilities and culture, whereby culture addresses the behavior and beliefs of single individuals and not the culture of the organization. In detail, the barriers have been mapped to four subcategories in the capabilities category: unfitting conditions, unfitting resources, missing responsibility, and missing knowledge. Similar to this, subcategories of the culture category have been derived: unwillingness, emotion, and missing critical thinking. The identified measures have been mapped to derive general core categories of measures. However, the data collected did not allow generalization to the impact of certain specific measures on specific barriers. Comparable to a metaphoric ship sailing through mapped barriers blocking its journey across the sea, the specific measures to overcome the barriers depend on a variety of contextual particularities – like type of ship, skill of the crew, or the weather. However, general core categories of measures to apply and adapt to the individual particularities can be provided to ease the journey. These core categories of measures have been derived and the seven categories have been mapped onto groups of barriers: demystification, building human capabilities, building data capabilities, building technological capabilities, building organizational capabilities, building procedural capabilities, and involvement and communication. Condensed to these core categories, the measures have presented a pattern of addressing capability barriers but have an indirect effect on cultural barriers. Addressing cultural barriers directly has rarely been observed. In the general idea of Analytics seeking objective evidence for decision-making, this fits the approach of creating convincing evidence of benefits and building the skills to experience these benefits to influence the beliefs about Analytics as opposed to addressing beliefs directly.

6.5.1 Managerial Implications

Managers in LSCM organizations can use the results of the study in a variety of ways. The systematization of barriers can be used to investigate individual Analytics processes and initiatives. The barriers might not be visible to them as they fail to realize benefits and value from their initiatives. Considering the barriers identified, managers are able to critically reflect on and analyze their initiatives and take action accordingly. In regard to the discussion above, managers can use these results to gain awareness regarding their Analytics initiatives.

In addition, measures can be derived to support applying Analytics initiatives for individual organizations. While this study refrains from recommending specific measures for certain barriers, managers can review the collected measures, evaluate the fit to the individual context of their organization, and apply them with according adaptions. The core categories of measures, which this study puts into focus while recommending deriving individually adapted measures from them, can further provide starting points for measures which can be used by managers to address barriers in their own organizations.

Managers should certainly become attentive to measures that can be used outside of specific Analytics initiatives. Organizational measures of establishing codes of conduct, allocating responsibilities, or organizing all affected business units to voice a harmonized request for investment and budget allocation, directly impact the quality of the Analytics initiative due to the existence of better resources. Furthermore, indirect measures such as the creation of informal exchanges amongst analysts (or among analysts and non-analytics employees) can lead to informal relationships and an overview of available skills and knowledge. This overview of available skills and relationships to access them can shorten reaction times or improve reaction quality if issues are encountered during Analytics initiatives requiring skills outside of the project team. If managers combine this with incentives to learn and test new approaches together, such as in communities of interest, the available range of skills in the organization may also improve.

Finally, while analysts may frequently not have the personality traits to relish the presentation of themselves and their results, this study emphasizes the importance of their results being presented to other peer groups. Thus, managers may need to identify presentable results and motivate analysts to present the achieved benefits, as well as providing them with occasions to present them. However, these occasions are not intended to "show off", but to motivate the creation of more and new use cases for Analytics that are beneficial and valuable to the organization.

6.5.2 Limitations and Further Research

As a limitation of this study, the low impact of the particularities of LSCM to the results of this study must be considered. More detailed insights on the integration of several business units along the flow of materials, the complexity of data collection of moving assets, and the cooperation with supply chain partners had been expected beforehand. Similarly, collaborations on use cases along the Supply Chain play a negligible role for LSCM organizations. Further, no implications from use cases crossing internal organizational lines have been observed. While this is regular in LSCM, it does not seem to increase the complexity of Analytics initiatives, as long as effective stakeholder management is in place. Expected technical issues, especially in data collection, are bypassed with proxies and reasonable means already at hand.

Another limitation is the exploratory nature of this research, which aims at identifying a wide range of effects and their relationships, but not their strength. The strength must be tested in confirmatory research.

Further, the interviewees declined to compare their barriers and measures to other domains, since they lack knowledge on other domains. As a result, this study can solely present the state of LSCM, but has no data to create a comparison with other domains.

Further research is required to identify contextual factors that moderate the impact of measures. Since organizations are currently limited in ideas, multi-actor use cases in Supply Chain Analytics need to be identified and their value investigated. Concerning the field of Analytics, further research into the single-source-of-truth is needed, including investigating trade-offs between the availability of data and the speed of processing it, as well as pathways to convergence of IT systems. In addition, the scarcity of analytical talent needs to be reevaluated.

7 Enabling LSCM organizations to use Analytics

This thesis states the mission of *providing guidance to enable organizations to use Analytics* by providing actionable insights. Thus, this chapter is providing *guidance* and insights oriented on managers of LSCM organizations. Hence, this chapter presents additional information and perspectives on collected data compared to the previous chapters. First, information about the collected data are summarized to critically reflect the scope of application and provide managers with means to assess, whether the results are valid for them. Regarding the SEP (section 1.2), this section contributes to stage 5 of evaluating the results for *corrective adjustments*. Following the leading theme of LSCM research as presented in section 2.1, the second section discusses the impact of Analytics on customer value. Third, a supplemented approach to manage SCA initiatives is presented to *guide* managers in the use of SCA. Since the articles that form the body of this thesis are oriented towards a scientific audience, these articles provide limited guidance to managers. Thus, the second and third section of this chapter represent the corrective adjustments to adhere to the mission of this thesis transferring the generated scientific insights to *guidance* for LSCM managers intending to manage SCA.

7.1 Scope of application

Several constraints limit the scope of application of this thesis. A research focus has been assumed to keep the research effort in manageable boundaries. Data collection was dependent on availability of primary and secondary data, and accordingly to the openness of organizations to research inquiries, which has been narrow since Analytics is perceived as means to achieve a competitive edge. The resulting scope of application is presented in this section to allow managers to assess, whether the results are relevant for them.

7.1.1 The focus of this thesis

The assumed research focus of this thesis is the management of Analytics in the context of LSCM, which comprises four aspects. First, it includes organizational factors of the execution of Analytics initiatives and surrounding initiatives, which can moderate the success and value generated from initiatives, such as infrastructure, motivation, collaboration, understanding of Analytics and the tasks involved. Second, the research focus includes an overview about what kind – archetypes – of Analytics initiatives are executed in context of LSCM. This creates understanding of opportunities, provides inspiration to create initiatives and specifies competences and technologies needed for Analytics. Third, the chosen managerial research focus includes practices most relevant on the success of Analytics initiatives from data to creating organizational value such as starting point, staffing, inclusion of externals, deployment actions, and performance preservations. Forth and finally, organizational barriers of Analytics, which occur most frequently in LSCM, are included in the managerial research focus on Analytics in context of LSCM. In addition, organizational measures, which managers can implement and apply, are complementing this. Concluding, the research focus understood as 'management of Analytics initiatives', assumed and investigated in this thesis, promotes Analytics as flexible tool that must be adapted to a chosen and specific LSCM problem and is influenced by a variety of factors and dependent in its success on the appropriate application of practices.

Opposed to this, a research focus that could have been assumed alternatively is on providing solution paths for specific problems in LSCM, paths for improving specific logistics performance indicators or about which model or algorithm is providing the most promising result for specific problems in LSCM. This research focus was rejected due to several perceived downsides. First, such a research focus would have been limited in the number of considered problems and their solutions paths due to ambiguity of the boundaries of LSCM and resulting ambiguity of which problems belong to it, the limited observability of unknown future LSCM problems, and limited resources. Second, considering specific LSCM problems would limit managers to understand the potential of Analytics as a flexible tool. The evidence collected emphasizes to approach problems in Analytics initiatives with an open mind in regard to the local specifics and individualities of a problem, to the hidden potential in the data, and to the requirements and needs of the intended users of an Analytics solution. These factors influence the analytical approach (data preparation, models, algorithms), the development of the solution and its successful deployment. Certain formulated paths to solve specific LSCM problems presumes certain data, technologies and process characteristics as well as maturity with technologies and Analytics. Managers could be inclined to pursuit Analytics initiatives in the narrow and comfortable choice of LSCM problems with formulated paths and neglect problems with higher criticality, while the evidence collected for this thesis presents Analytics with a paradigm of prioritization by criticality, urgency and value. Third, such paths might be produced and established in an organization over time but cannot be transferred without loss in validity to other organizations. Fourth, the success of these paths would further be moderated by contextual and situational factors of organizations, their IT ecosystems and their workforces. The flexibility of Analytics and the moderating organizational factors, which are argued in this thesis to be necessary for creating competitively superior solutions, are not covered in such a research focus on specific LSCM problems and their solution paths.

A third relevant research focus, which could be argued as valid option for being assumed in this thesis, is the development of an Analytics solution for a specific LSCM problem. This would, however, be an operational focus as opposed to a managerial focus as intended for this thesis. While such an approach is relevant and needed for several problems in LSCM, managerial recommendations resulting from such a focus would be limited to the data collected on the one LSCM problem considered, and would be dependent on investigating the problem from definition to maintenance. It would omit to understand Analytics for its flexibility and the impact of diverging from the practices employed for the one problem.

7.1.2 The scope of data collection

The intended scope of application of this thesis are organizations with LSCM activities as their core business model such as LSPs, and organizations with LSCM functions in their organizations to fulfill their material and informational flows, such as manufacturers and retailers. In this thesis, these organizations have been labeled as *LSCM organizations*. As an important note for the scope of application, some LSCM organizations have created spin-off organizations for their Analytics needs, since they have recognized the potential to sell the services to other organizations. These spin-off organizations are recognized as Analytics providers in this thesis. However, the accessibility of these organizations for data collection is limited and differs for several reasons. First, Analytics is a novel topic and the number of relevant LSCM organizations to collect data from is limited. Second, Analytics may not be a designated function with recognizable job titles in these organizations, what complicates the effort to identify relevant experts for primary data collection. Third, these experts are quite demanded and busy with the topic and are usually not able to spend their time for scientific inquires. Fourth and finally, a very problematic factor for this thesis is the unwillingness to share information, since organizations that are mature in Analytics also perceive it as important factor in competition and their practices are held confidential – no matter whether anonymity is assured, and the focus is not on specific Analytics Solutions or initiatives. Considering the collected evidence, this level of desired confidentiality is amplified by the circumstance that organizations contemporarily focus on internal improvements with SCA and produce advantages invisible to competition and thus not imitable. Resultingly, for every interview conducted with an expert, on average 5,84 interview requests have been sent, not counting additional undocumented and informal requests or reminders. As presented below, only two interviews with experts in retail were conducted despite multiple attempts. In the remainder of this section, each research inquiry is considered individually, and critical aspects are discussed.

For the first article, "Mapping Domain characteristics influencing Analytics initiatives", twelve interviews have been conducted with thirteen experts. Due to the focus of the article, experts from Analytics service providers were inquired for interviews. The interviewees had experience with LSPs, retail and manufacturing organizations but were explicitly inquired for their experience in a variety of domains to allow comparison of LSCM to other domains. Requested SCA experts in LSCM organizations have repeatedly explained they would not be able to make comparisons, since their experience is limited to one domain. Thus, these experts have been excluded from this data collection. Table 4 lists the interviewed experts. The organizations of the experts are kept anonymous, as

No.	Background	Function/Job Title	Experience in Analytics [yrs]	Duration of interv. [min]
1	Analytics Provider	Data Scientist	21-25	40
2	Analytics Provider	Director Analytics	16-20	25
3	Analytics Provider	Data Scientist	6-10	50
4	Analytics Provider	Director Analytics	16-20	65
5	Analytics Provider	Manager Analytics	16-20	60
6	Analytics Provider	Director Analytics	26-30	50
7	Analytics Provider	Head of Analytics	31-35	45
8	Analytics Provider	Head of Analytics	16-20	N/A
9a	Analytics Provider	Manager Analytics	6-10	65
9b	Analytics Provider	Manager Analytics	1-5	N/A
10	Analytics Provider	Sen. Manager Analytics	21-25	55
11	Analytics Provider	Manager Analytics	6-10	55
12	Analytics Provider	Manager Analytics	21-25	60

Table 4: Overview of interviewed experts for article 1

ensured to the experts. Their function or job title is harmonized to refer to Analytics, except for Data Scientists, to further disguise the experts. Additionally, the experience with Analytics is displayed in ranges of five years as additional measure of anonymity. The same approach will be taken for displaying the interviewed experts of the third and fourth article.

For the second article, “Archetypes of Supply Chain Analytics”, secondary case studies have been analyzed. The affiliation of the cases to the groups of organizations explained above are presented in Figure 28. Concerning the allocation of the groups of organizations to the six identified archetypes, no imbalance has been observed in the data.

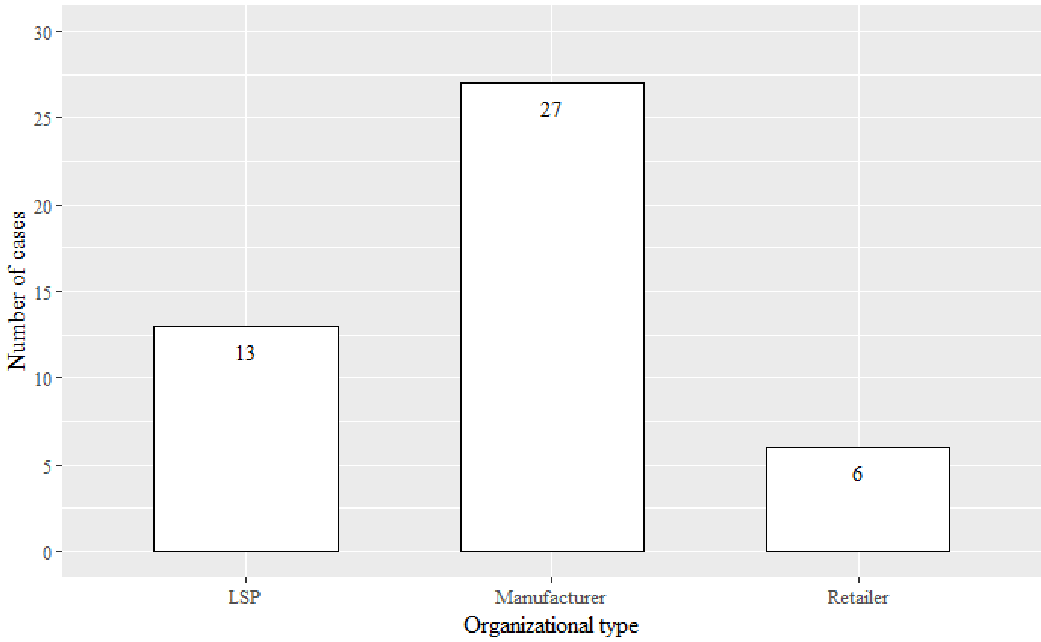

Figure 28: Overview of cases for article 2

Regarding the purpose of article 3, “Explaining the Competitive Advantage generated from Analytics with Knowledge-based view”, a strong focus on LSCM was assumed in the conducted case studies. For this purpose, LSCM organizations have been inquired. Further, case studies from Analytics providers with extensive experience with LSCM were inquired based on the Analytics providers’ focus on LSCM. Considering the Analytics providers, two were having LSCM organizations as their single customer group, and the other two, which were larger and more established providers, were having LSCM as one of the core customer groups and an extensive portfolio of LSCM specific services. Due to case organizations not being able to provide more than one expert for interviews, the data was supplemented by an extensive search for documents. This resulted in 235 documents, consisting of 197 text documents including organizational

No.	Background	Function/Job Title	Experience in Analytics [yrs]	Duration of interv. [min]
1	Analytics Provider	Head of Analytics	11-15	50
2	Analytics Provider	Director Analytics	11-15	50
3	Manufacturer	Sen. Manager Analytics	1-5	55
4	Analytics Provider	Sen. Manager Analytics	6-10	60
5	LSP	Head of Analytics	1-5	60
6	Manufacturer	Sen. Data Scientist	6-10	50
7	Manufacturer	Sen. Manager Analytics	1-5	65
8	Analytics Provider	Sen. Manager Analytics	16-20	90

Table 5: Overview of interviewed experts for article 3

reports, organizational presentations, organizational whitepapers, organizational articles, organizational press releases, third-party reports and third-party articles as well as 38 videos including interviews, presentations and media material of about 14,3 hours. The experts and case organizations are presented in Table 5.

The fourth article, "Overcoming Barriers in Supply Chain Analytics", demanded a strong focus on LSCM as well. Resultingly, recruitment efforts were strongly focused on experts in SCA, which are active in LSCM organizations. Except for two experts, this focus has been kept. As explained in the article, the group of interviewees represents a broad variety of backgrounds regarding the Supply Chain including suppliers, OEM manufacturers, transportation LSPs, storage LSPs and retailers. Table 6 provides anonymized details on the interviewed experts. However, in view of the difficulties described above in recruiting Analytics experts for interviews, it should be emphasized once again that the strong focus on LSCM organizations has led to significantly lower response rates to interview requests as opposed to the previous data collections.

A standing critique of this thesis on Analytics applied to LSCM is the extensive collection of data from Analytics providers to the detriment of collecting data from LSCM organizations. While the unwillingness of experts of these LSCM organizations has been addressed twice already, two more aspects must be discussed to underline the relevance of the interviewed experts of Analytics providers. First, amongst the selected organizations are spin-offs of LSCM organization legally representing different organizations, which focus on providing Analytics solutions to LSCM organizations. Per

No.	Background	Function/Job Title	Experience in Analytics [yrs]	Duration of interv. [min]
1	Analytics Provider	Data Scientist	1-5	60
2	LSP	Data Scientist	11-15	50
3	Manufacturer	Manager Analytics	6-10	105
4	Manufacturer	Director Analytics	6-10	75
5	Manufacturer	Manager Analytics	1-5	55
6	LSP	Sen. Data Scientist	1-5	55
7a	LSP	Head of Analytics	6-10	60
7b	LSP	Head of Analytics	1-5	N/A
8	Retailer	Manager Analytics	11-15	85
9	Retailer	Manager Analytics	1-5	60
10	Manufacturer	Data Scientist	1-5	60
11	Manufacturer	Head of Analytics	15-20	50
12	Analytics Provider	Data Scientist	1-5	45

Table 6: Overview of interviewed experts for article 4

definition, these organizations are Analytics providers and have been labeled as such in the summaries above. The experience from experts of these organizations should not be misunderstood as Analytics expertise without domain expertise. Ironically, the reality is somewhat the opposite for these organizations as they use their LSCM experience to better position themselves in the market of providing Analytics solutions to LSCM organization than established Analytics providers. The ability for organizations to create these kinds of Analytics-oriented spin-offs and selling their services to less sophisticated LSCM organizations further displays a gap of expertise and maturity on Analytics in the domain of LSCM, which leads to the second aspect. As LSCM organizations have only begun to build Analytics business units in recent years, the available experts in these business units usually have a short experience horizon. The data summary displays this situation with the anomalies of successfully advanced Business Intelligence and Operations Research units. Prior to building these Analytics units, organizations had to contract Analytics solutions from Analytics providers. A status-quo, which is still valid for a multitude of LSCM organizations. Thus, besides their more extensive experience these experts from Analytics providers have exclusive insights into LSCM organizations without designated Analytics units and before such units were set up. This represents a vital insight for understanding the maturation of LSCM organizations in Analytics and is therefore crucial for this thesis.

Putting the sources of data into perspective, the results are noticeably stronger focused on manufacturers and LSPs using Analytics for their LSCM activities. The amount of data on retailers is low. Managers in retail intending to manage SCA should be aware of this. However, putting the results of the research in comparison, there are only minor differences between management recommendations between Analytics providers and the LSCM organizations. Further, the characteristics, which are more relevant to LSCM setting it apart from other domains in executing Analytics initiatives, have been identified as the crossing of organizational borders in Analytics initiatives, a tendency for heterogeneous data, the use of mobile sensors due to moving assets, a higher weight on the efficiency objective, and a more frequent use of prescriptive and (real-time) descriptive methods. These characteristics are firmly related to the material flow and should be equally relevant for retailers. Apart from that, the domains show differences in their specific use cases and how they must be solved methodologically. Thus, the results of this thesis show high relevance for managers intending to apply Analytics for retail as well.

7.2 The value for the customer

As explained in section 2.1, especially the literature stream of Logistics in the LSCM literature strongly emphasizes that LSCM activities must be oriented on the customers' needs and requirements. Evidently, the use of Analytics must result in improvements for the organizations' customers. Thus, this section discusses how SCA contributes value for the customers, provided the management of SCA is appropriate. Below, customers may refer to either end consumers or business customers. The presented discussion is not exhaustive but intends to highlight the variety of forms customers can gain value from organization applying Analytics to their LSCM processes.

7.2.1 Indirect value for the customers

Apparent from the evidence collected for this thesis, contemporary organizational SCA initiatives primarily focus on process improvements. These initiatives are not addressing customer needs directly. However, they have an indirect effect on customers. While a reoccurring topic in the discussion with experts has been the difficulty of displaying the impact from Analytics, a recommendation for managers is to think from the customers and the indirect impact on them, when they design their SCA initiatives and estimate the benefit. The following discussion may stimulate these thoughts.

The customers' perceived service **reliability** of LSCM services can improve indirectly from Analytics. Generically explained, improving planning under consideration of various disruptive factors and increasing robustness due to improved understanding and transparency enabled by Analytics solutions will affect the reliability of LSCM services. Two prominent and tangible examples are predictive maintenance and disruption recovery. Considering predictive maintenance, it usually concerns the prediction of maintenance needs of manufacturing machines, which disrupt operations with ill-fitting downtime. More relevant for LSCM are the maintenance needs of vehicles such as trains, trucks or aircrafts. Due to these assets moving through logistical networks, an unexpected downtime leads to asset recovery or transportation of maintenance crews, what increases the time to repair. Applied predictive maintenance allows the consideration of maintenance needs in fleet operations plans with assets in predicted need of repair ending their routes in repair shops. Thus, the direct effects are less disruptions of operations and an improved fit of plan to execution. Customers benefit indirectly from their shipments being less affected by disruptions or, in case of public transport, their means of transport adhering closer to schedule. As second example, disruption recovery creates plans to recover from disruptions due to next best solution optimization or testing of a variety of scenarios. Interviewees explained it as counter-intuitive behavior, since people in LSCM are not only interested in the optimal solution of an optimization problem as opposed to other domains but exploit the models for further business questions. Next best solutions are the best solutions on the condition of few changes to the original solution. They allow recovery from short-term changes of crucial factors in planned operations with the plans execution already set in motion. Further, scenario analysis is an alternative use of existing optimization models, which stress-tests the operations described by the model such as a supplier network. The scenarios help to assess several situations of disruptions and develop recovery plans before the disruptions occur. In both cases, the recovery from disruptions is enhanced as a direct effect for the organization, such that a reliable service stays available as indirect effect to customers.

Customers' perceived **service quality** of LSCM operations is indirectly affected by SCA initiatives addressing the process efficiency (e.g., detection of unexploited potential or deficiencies). These initiatives are primarily aimed at improving processes in general rather than adapting process efficiency to customers' needs (see 7.2.2). However, these improvements change process characteristics such as process times or error-rates, that are eventually perceived by the customers. Two examples for such analytical actions are process analysis and real-time monitoring. First, process analysis is an established tool in LSCM, which can be supplemented by Analytics. Identifying bottlenecks, errors, or factors that contribute to quality or performance degradation can be supplemented by Analytics, if data collection is possible. However, this usually requires design changes that must be implemented and tested to exploit the identified potential. Increased efficiency and reduced deficiencies directly impact an organization's process performance but are eventually also indirectly perceived by the customers employing services related to that improved process. Second, transport monitoring allows to reduce issues of drivers taking large unplanned detours and unplanned stops resulting in delayed shipments. These delays usually affect operations of manufacturing organizations requiring their shipped material for manufacturing goods and products. Monitoring shipments, revealing unplanned activities and terminating them directly results in improved timeliness of the LSCM organization offering the service. Indirectly, the perceived increase of the service quality of shipments increases the value for the customers.

Customers can indirectly gain value from reduced costs of processes and operations. A leading theme throughout the collected evidence is the relevance of a positive return-on-investment for an Analytics initiative to be carried out. Thus, process improvements from Analytics initiatives must be accompanied by **cost reductions**. Besides, SCA initiatives also primarily address cost reductions. Provided that organizations pass cost savings on to their customers, these customers can indirectly benefit from such initiatives. Reduction of procurement costs and cross selling/up selling are two examples for this. First, the relevant data to consider for reducing procurement costs may not necessarily be prices of procured goods. With Analytics, the focus can be pivoted from prices to lifetime cost of the goods. In addition, economies of scale or scope can be identified due to analyzing orders of several business units and creating new allocations of orders to suppliers and aggregating shipments across orders. Extended to a holistic optimization, the sum of warehouse, transit, transaction and various other costs can change the procurement strategy from lowest prices to lowest total cost. Eventually, analysis of supplier performance can be used in contract negotiations. However, strategic partnerships should have priority over such actions. Resultingly, Analytics can directly reduce the procurement costs of goods, which can be passed on as indirect value to customers. Second, cross selling/up selling refers to offering goods to customers they are likely to demand in the future or to procure from other organizations already. While such Analytics solutions (e.g., recommender systems) are intended to increase the profit of applying organizations, they can create economies of scale and scope in procurement, manufacturing, and transport due to adapted orders from customers. The direct cost savings from these effects for organizations can be passed on to customers, indirectly providing them value from the Analytics solution of the LSCM organizations.

7.2.2 Direct value for the customers

The direct value for customers from SCA is provided by customer facing Analytics solutions on LSCM problems or by new offerings for customers enabled by Analytics solutions. These solutions provide services that extend physical services by adding relevant information and functionality beneficial to customers. Thereby, the collected evidence emphasizes the migration of data-driven services from the consumer market to the business market, such as e-commerce services of shipment tracking and ETA predictions. Business customers can use these solutions to improve their own operations. LSCM managers are recommended to observe Analytics-based innovations in the consumer market for increasing the service portfolio of their organizations.

The **operations efficiency** of customers directly benefits from Analytics Solutions provided by LSCM organizations. Customers improve efficiency and gain value due to transparency, which they use for planning and executing their operations, and by increased flexibility from novel Analytics-based services, which allows them to adapt operations to changed situations. Two examples for direct value of this form are tracking and tracing solutions for customers and LSCM services based on dynamic routing. First, tracking and tracing solutions allow customers to react faster on changed conditions of their shipments. Delays or premature shipments can be encountered with adapted operations or reordered goods with faster shipping options. Thereby, the reactions and subsequently efficiency improvements depend on the features of the Analytics solution. For example, alerts raise attention to changed conditions to trigger reactive responses, while predictions allow proactive responses. Further, the level of detail ranges from passed locations of a shipment to its exact position and physical status, while the latter allows faster reactions on damaged shipments with resultingly reduced effects on customers' operations. Second, dynamic routing allows LSCM organizations to provide new services to customers. Dynamic delivery services allow customers to receive shipments appropriate to their operations instead of adhering to static routes. Besides consumers, the service can be relevant for business customers only operating at certain times of the day (e.g., restaurants) or leaving for home visits (e.g., craftsmen). Dynamic pick-up services enable customers to adapt their shipments to the operations, such as moving the shipment backward in time on heavy workload or the other way around. In both services, customers strongly benefit from the provided information (or rather estimations) about the status of the LSCM organizations vehicles.

An aspect that can be improved in a twofold manner is **time**. Time can address the lead time between customers placing their request for products and services and the successful fulfillment of the request, which can be shortened due to SCA. It can further address the timeframe customers have to reserve for receiving a service, which can be shortened as well. In both cases, shortening the time provides directly value to customers. Two examples relevant for the aspect of time are anticipatory shipping and improved accuracy of ETA predictions. First, despite the fictional sounding vision of providing customers with products before ordering them, as presented by the patent-holder of anticipatory shipping (Amazon), the concept is already implemented in a less intrusive form. Opposed to sending shipments to customers before ordering, products predicted to be ordered are already transferred to distribution centers near the customers, who are predicted to order them. Resultingly, the travel time to the customer is reduced in case of an order providing them with a time benefit. Second, providing an ETA to customers is an alternative to provide detailed transparency over moving assets (see tracking and tracing), if this level of detail is unwanted such as with consumers. While an ETA prediction allows similar adoption of operations as discussed above, it creates particularly value for receivers unable to use the timeframe of waiting for alternative activities. Especially, consumers of delivery service of modern business models (e.g., delivery of groceries or beverages) are limited to wait at home for their delivery during the agreed timeframe. Accurate ETA predictions eventually allow to shorten the communicated timeframe consumers must reserve for waiting. In this case, the Analytics solution provides a direct time benefit to consumers.

Finally, while no customer facing Analytics solution is employed, the **availability of products and services** can be improved with customer-oriented solutions. One of the earliest uses of SCA is demand prediction to the provision of demanded products to customers. Today, it is one of the most developed and widely used applications. Any product or service customers want to consume, requires its availability, and Analytics improving availability resultingly leads to direct benefits for customers. The finally presented two examples for improving availability with Analytics are demand forecasting and shelf stock-out prediction. First, demand forecasting predicts the demand for a product or service in a certain time and location. Different aggregation levels of time and location are used for different decisions eventually leading to products or services being available when and where the customers want to procure them. Inaccuracy of demand forecasts lead either to non-availability of products and services, which is dissatisfactory for customers, or products being over-stocked generating additional cost in perished products, tied capital and storage costs, which are passed on to the customers dissatisfying them in the future. Thus, increasing the accuracy of demand forecasts with Analytics is directly valuable to the customers. Second, the prediction of shelf stock-outs affects product availability to customers in retail stores, because shelf capacity is limited and replenishment from storage areas may not keep pace with the procurement rate of the customers. Usually, no depletion signal of the shelf availability is collected except the sales transactions of products, which arrive delayed. Further, shelf replenishment is also usually not electronically collected. Resultingly, the visibility of the stock level on the shelf is missing and customers experience products as unavailable which are on stock in the storage area. Analytics can be used to predict shelf stock-outs, which trigger replenishment orders and reduce the number of dissatisfied customers. Hence, customers gain value from product availability.

7.3 An approach to manage Supply Chain Analytics initiatives

As explained by interviewees, Analytics constantly goes through changes of labels and names based on new emerging methods or technologies enabling new or larger scaled use cases, more accurate analytical results, and higher performance of analytical calculations. Besides, these new labels are usually accompanied by newly formulated approaches to Analytics. However, as criticized by Franks (2014), these approaches are basically identical to the Cross-industry standard process for data mining (CRISP-DM), which has been developed in the end of the 1990s (Chapman et al., 2000). In the following section, the procedure of deriving an approach to manage SCA is explained. Thereby, a supplemented CRISP-DM approach is developed including the practices and insights collected particularly from the domain of LSCM. The development was chosen as opposed to a specific SCA initiative approach, as explained below. Further, a comparison and alignment of process models is conducted and presented. Subsequently, the derived supplemented approach is presented and explained. Finally, the supplemented approach is applied to an SCA initiative to evaluate the results of this final analysis, which is consistent with stage 5 of the SEP underlying this thesis (see section 1.2).

7.3.1 Motivation and procedure of deriving an approach to manage Supply Chain Analytics initiatives

As indicated, other approaches to Analytics initiatives are highly similar. However, they differ in the number and names of phases concealing the similarity. This leads to confusion for managers intending to manage their Analytics initiatives, while labels and names conflict and overlap. Since the mission of this thesis is to provide *guidance* (see section 1.2), the creation of yet another approach for managing Analytics initiatives is not considered as valuable because it is likely to contribute to confusion instead of dissolving it. Besides, Analytics has been clearly established as a flexible tool, which is "very transmissible" to various domains as an interviewee responded. To develop an approach for managing Analytics initiatives for one specific domain contradicts this flexibility and transmissibility and, thus, the results of this thesis. This thesis specially criticizes research on Analytics that claims progress on Analytics to be limited to a focal domain and ignores progress in other domains, while it could be transferred, valuable and problem-solving to the focal domain. An approach to manage Analytics initiatives focused on the domain of LSCM would only emphasize such enclosed thinking, while the generic approach chosen to be developed in this research is supposed to be inviting managers in the domain of LSCM to look beyond their domain when intending to generate value with Analytics initiatives. In addition, the practices and insights collected from the domain of LSCM, which are used to supplement the approach of managing Analytics initiatives, can provide value in other domains. In developing a generic approach, these practices are more likely to be recognized by scholars and practitioners in other domains as opposed to a domain-specific approach. Resultingly, the approach to manage SCA initiatives presented below is specifically kept generic as supplement to the CRISP-DM approach in favor of a specific SCA approach.

In the interviews, the CRISP-DM approach was frequently named as the preferred approach to manage Analytics initiatives in the interviewees' organizations. Due to this

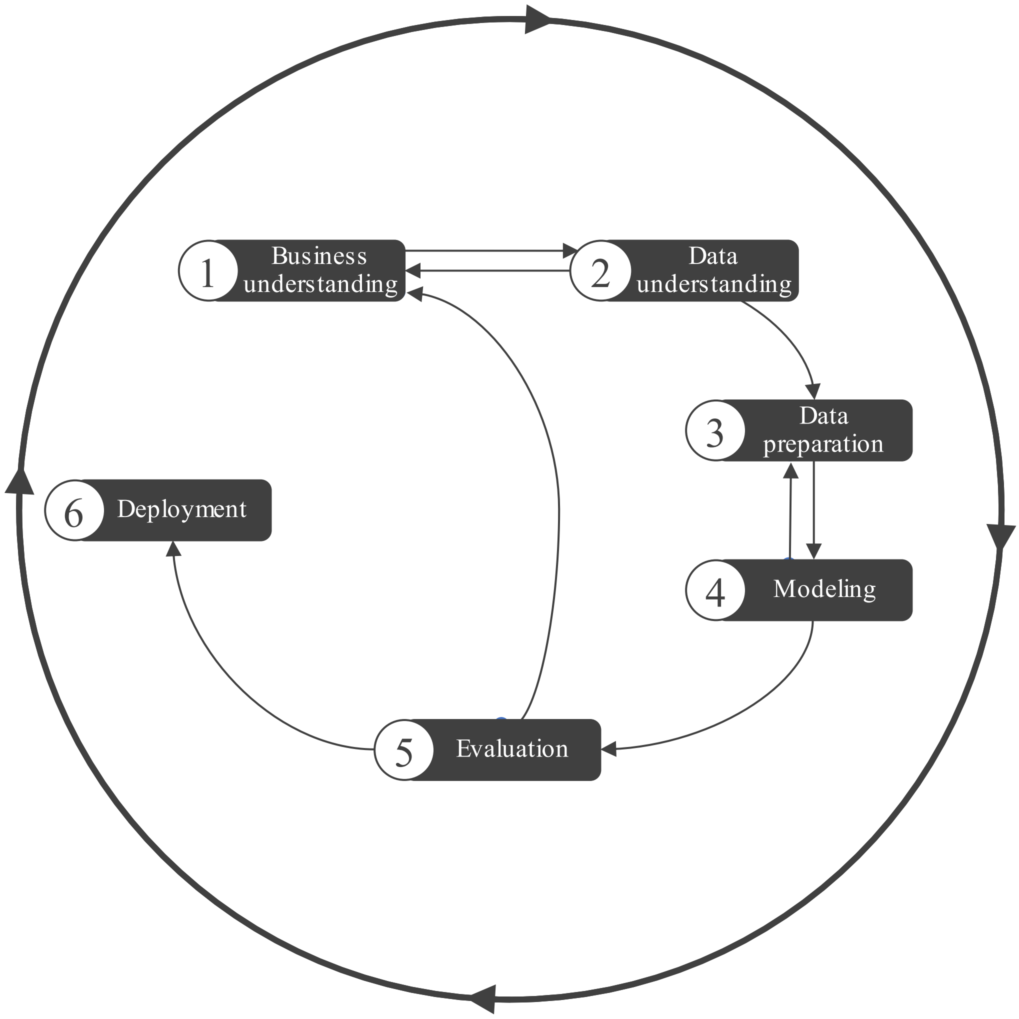

Figure 29: CRISP-DM approach to Analytics initiatives (Chapman et al., 2000)

general broad recognition and the favorable recognition in the interviewed organizations, it was chosen as central approach to manage Analytics initiatives to be supplemented in this thesis. The CRISP-DM approach consists of six phases as illustrated in Figure 29. The sequence of the six phases describe the inner circle. The arrows are not solely directed forward but additionally describe the most important and frequent loops. In other words, revisiting phases in an Analytics initiative is not uncommon due to changing conditions or encountered obstacles, e.g., from issues with data as repeatedly mentioned in the interviews. Besides these most frequent loops, any kind of loop might occur and should be allowed if conditions require it. The outer circle is supposed to symbolize the cyclical nature of Analytics, with additional actions after the deployment of Analytics solutions including the invention of new use cases based on the experiences from developing the solution as particularly explained by Chapman et al. (2000). Considering the deployment phase, the outer circle could further indicate the execution of maintenance and monitoring actions, which are supposed to be planned in the deployment phase. However, this is not specifically mentioned by Chapman et al. (2000). As indicated above, to provide the intended guidance and dissolving of confusion between the multitude of approaches to Analytics initiatives, the CRISP-DM approach (Chapman et al., 2000) is compared to fourteen additional approaches to manage Analytics initiatives. This shows how the approaches overlap as well as it closes gaps of the CRISP-DM approach. The considered approaches are presented in the following list. The interested reader may refer to Appendix A for extensive details:

(1) Knowledge Discovery in Databases Process (Fayyad et al., 1996)
(2) Steps involved in using advanced analytics (Bose, 2009)
(3) The [process-application-data-insight-embed] PADIE Technique for operationalizing Analytics (LaValle et al., 2010)
(4) Meaningful data integration (Bizer et al., 2012)
(5) Outline of big data analytics in healthcare methodology (Raghupathi and Raghupathi, 2014)
(6) The Professional Job Task Analysis Process (INFORMS, 2014)
(7) Framework for implementation of Big Data projects in firms (Dutta and Bose, 2015)
(8) Operations Research Modeling Approach (Hillier and Lieberman, 2015)
(9) Mayor's Office of Data Analytics 10 step model (Copeland, 2015)
(10) The life cycle view of statistics (Kenett, 2015)
(11) Data Analytics Lifecycle (Dietrich et al., 2015)
(12) Fast Analytics/Data Science Lifecycle (Larson and Chang, 2016)
(13) Data analytics lifecycle model (DALM) (Song and Zhu, 2016)
(14) [Sampling, Exploring, Modifying, Modeling, and Assessing] SEMMA (SAS, 2017)

In Addition, this thesis has collected a variety of data on managing Analytics initiatives in the domain of LSCM. While few practices and insights are unique to LSCM, the collected practices and insights are highly relevant to the domain of LSCM since they have been particularly collected from or in reference to the domain. Thus, the practices and insights collected are likely to be relevant to other managers in LSCM interested in managing Analytics initiatives in the sense of the vision of this thesis – enabled to execute Analytics such that it creates sustainable competitive advantage and continuous improvement of processes and customer satisfaction. Considering the four inquiries of this thesis, the practices and insights include information on initiatives influential factors, purpose and objectives, value and (competitive) advantage creation, and measures to overcome barriers investigated with focus on the domain of LSCM. Hence, the complete evidence collected for this thesis has been reviewed and analyzed for relevant practices and insights that could further supplement the CRISP-DM approach. Since the fourth article specifically investigated practices, which were, however, only presented in an aggregate form, the interested reader may refer to Appendix B listing and describing the collected practices. The resulting supplemented CRISP-DM approach (sCRISP-A) consequentially represents a proven approach for managing Analytics initiatives, in particular including SCA initiatives, due to updates through insights on managing Analytics initiatives since 2000 and practices particularly relevant to LSCM and, thus, managing SCA. Thereby, the introduced abbreviation of "sCRISP-A" updates the outdated "data mining" term with "Analytics".

7.3.2 Comparison of approaches to manage Analytics initiatives

The CRISP-DM approach is extensively explained by Chapman et al. (2000) with a motivation of the overall approach and individual sub-chapters for each phase in three variations (general approach, user guide, outputs) including obstacles to be aware of. This level of detail is only matched by few of the considered approaches. Further, the CRISP-DM approach is clearly focused on Analytics initiatives. This is equivalent to most approaches it was compared to. The summary of these characteristics of the analyzed approaches is presented in Table 7. The numbering starts with zero, since all approaches are compared to the CRISP-DM approach (No. 0).

Considering the general sequence of tasks, the compared approaches usually concur with the sequence described in the CRISP-DM approach. Only two approaches recommend a slightly different sequence of tasks. First, The Knowledge Discovery in Databases approach (Fayyad et al., 1996) puts the data preparation phase previous and parallel to the data understanding phase. This approach is the oldest approach in the set of compared approaches and has been included explicitly due to its age and first-mover characteristic. Considering anecdotes of the interviewees during the data collection, database conventions have changed considerably over time. Thus, this difference was interpreted as artifact of these database conventions demanding preparation of data before any understanding of it could be attempted. Second, the MODA's 10 step model (Copeland, 2015) puts the task of formalizing an agreement between user and analysts after the data understanding phase instead of the end of the business understanding phase. The source emphasizes to test, whether data is accessible and can be used for the intended purpose before formally agreeing on the Analytics initiative's focus. This approach is presented by the Analytics unit of the City of New York, which has established a data sharing platform. The existence of this platform was interpreted to reduce the effort of accessing a dataset for the explained testing. This might not be imitated by other user-analysts-relationships, which demand a formal agreement guaranteeing compensation for the cumbersome data understanding phase. The sequence of phases is presented in Figure 30.

No.	Name	Description of phases	Focus
0	CRISP-DM	Individual sub-chapters	Initiative
1	Knowledge Discovery in Databases	Paragraphs	Initiative
2	Steps involved in using advanced analytics	Key points	Initiative
3	PADIE Technique	Paragraphs	Value creation
4	Meaningful data integration	Paragraphs	Initiative
5	Outline of big data analytics in healthcare methodology	Key points	Initiative
6	Job Task Analysis Process	Individual sub-chapters	Initiative
7	Framework for implementation of Big Data projects in firms	Paragraphs	Initiative
8	OR Phases	Individual sub-chapters	Initiative
9	MODA's 10 step model	Paragraphs	Initiative
10	Statistics live cycle	Individual sub-chapters	Initiative
11	Data Analytics Lifecycle	Individual sub-chapters	Initiative
12	Fast Analytics/Data Science Lifecycle	Paragraphs	Initiative
13	The eight-step data analytics lifecyce model	Key points	Initiative
14	SEMMA	Key points	Data analysis

Table 7: Characteristics of compared approaches to manage Analytics initiatives

The number of phases ranges from a minimum of three to a maximum of eleven phases. This difference does not necessarily originate from a difference in tasks but a difference in condensing tasks to phases. While the PADIE Technique (LaValle et al., 2010) condenses several tasks into its first phase, which are spread over four phases in the CRISP-DM approach, the Framework for implementing Big Data projects in firms (Dutta and Bose, 2015) considers every task the CRIPS-DM approach condenses to the business understanding phase as individual phase. The approaches with such wide-ranging phases as compared to the CRISP-DM approach, such as the PADIE Technique, coincide with less detailed descriptions and result from less detailed considerations and number of tasks.

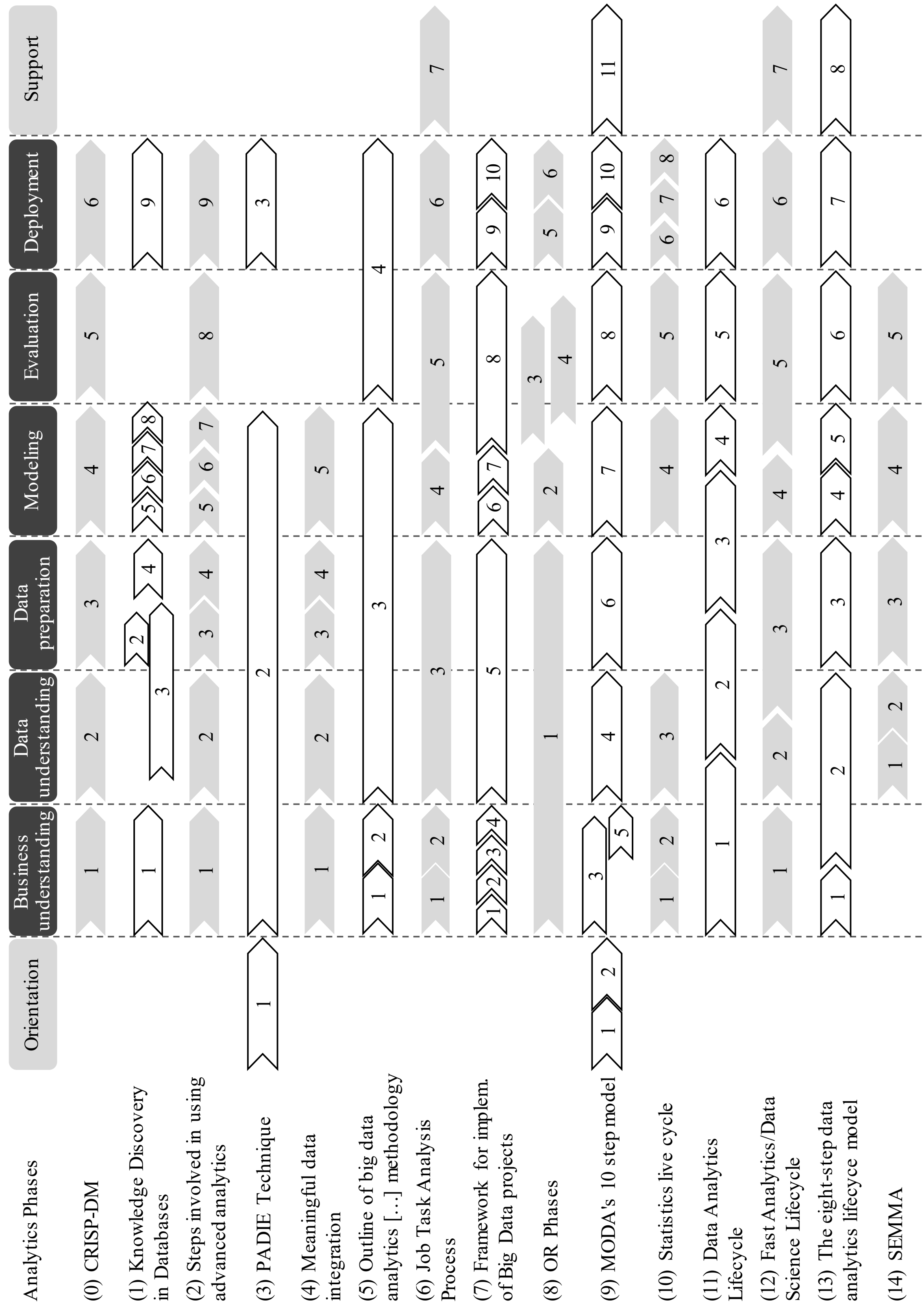

Figure 30: Comparison of sequence, number and scope of phases of management approaches to Analytics initiatives

In contrast, the very detailed described approaches condense the tasks to a number of phases similar to the CRISP-DM approach. Phases in a range of six to eight appear to be more reasonable condensations of tasks as well as they are more memorable. The number of phases is presented in Figure 30.

The scope of tasks in the compared approaches is usually similar to the scope of the CRISP-DM approach but a multitude of small differences occur. Several approaches lack tasks recommended in the CRISP-DM approach. This is due to various reasons. First, the level of detail of the approaches' descriptions is low such as in the PADIE Technique (LaValle et al., 2010). Second, the tasks is somewhat implicit in the described tasks such as evaluation phase might be implicit in the various modeling tasks of the Knowledge Discovery in Databases approach (Fayyad et al., 1996). Third, the focus of the approach varies from the focus of the CRISP-DM approach, such as the SEMMA approach (SAS, 2017) focusses on data analysis resultingly ignoring the business understanding and deployment phases. Gaps are presented in Figure 30.

Remaining with the consideration of the scope of tasks, more importantly for this analysis are the tasks not covered by the CRISP-DM approach but other approaches. These come in different forms. Several tasks are added, altered or explained more detailed in other approaches. These tasks are subject to the next section and will be considered below. Further, several approaches describe tasks outside of the scope of the CRISP-DM approach. Tasks that precede the business understanding phase have been aggregated to a phase, which was named "orientation" in alignment with the results of the fourth research inquiry of this thesis. These tasks include the documentation and analysis of processes as well as understanding, how Analytics can support these processes (Copeland, 2015; LaValle et al., 2010). Specific tasks subsequent to the deployment phase were aggregated to a phase labeled as "support" due to their supporting and maintaining nature of the Analytics solution. These tasks match the idea of the "outer circle" of the CRISP-DM approach, but are more specific and detailed emphasizing the necessity of including these tasks in the initiative. These tasks include determination of long-term responsibility for the Analytics solution, long-term evaluation of the Analytics solution's value, collection of long-term feedback for adjustment and improvement and its performance monitoring (Copeland, 2015; Dutta and Bose, 2015; Larson and Chang, 2016; Song and Zhu, 2016). The scope is presented in Figure 30.

7.3.3 A supplemented CRISP-DM approach to manage Supply Chain Analytics

This section introduces the sCRISP-A approach, which is recommended to be used to manage SCA initiatives. It has been developed from the introduced set of compared approaches to manage Analytics initiatives and the data collected for this thesis. As indicated above, the sCRISP-A consists of a total of eight phases, which include the tasks originally included in the CRISP-DM approach, supplements and adjustments to these tasks as well as one phase with additional tasks preceding and one phase with additional tasks following the original approach. An overview is provided in Figure 31. Due to the support phase replacing the outer circle of the graphical representation of the CRISP-DM, the outer circle is excluded from the figure. The dashed line represents ideas and experience developed during the Analytics initiative directly initiating new use cases and presentable value and benefits of the Analytics solution used as originator of ideation processes in receptive business units. The phases and the corresponding tasks will be briefly presented in the subsequent sections.

Readers are advised on the subsequently used taxonomy: The highest level of entities discussed in the sCRISP-A is termed as "phases", of which eight are distinguished. The next lower level of hierarchy is termed as "tasks". The phases consist of three to five tasks. The last and lowest hierarchy level in the taxonomy is "actions". The number of actions per task vary and are aggregated to content-related key points.

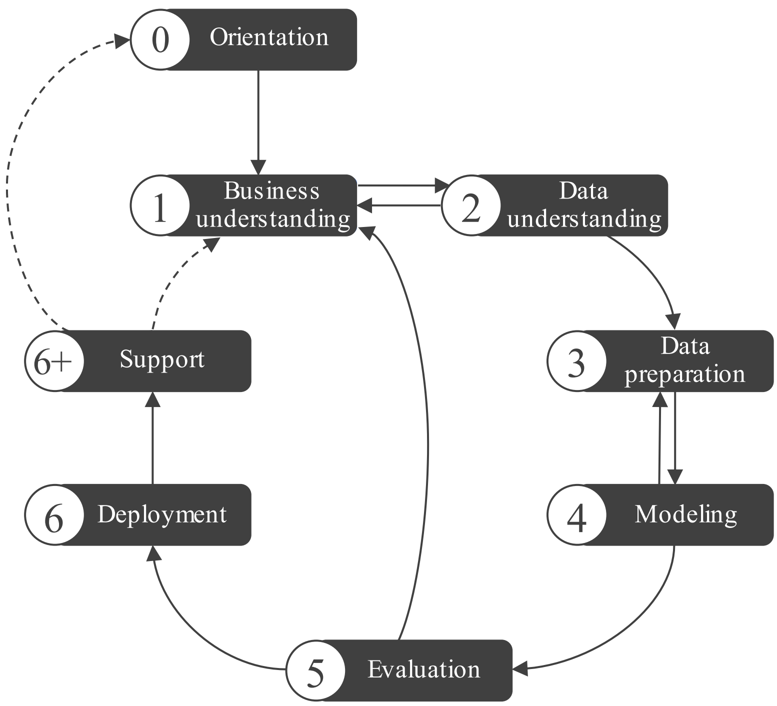

Figure 31: Overview of the sCRISP-A to manage Supply Chain Analytics initiatives

7.3.3.1 Phase 0: Orientation

The orientation phase ensures to identify the business areas with the highest impact of Analytics on the competitive position, alignment of Analytics activities with this competitive actions, fulfillment of the relevant requirements of these Analytics activities and the identification of use cases in the respective business units. These four tasks of this orientation phase are detailed in Table 8. Descriptions in square brackets '[]' represent alterations resulting from the validation (section 7.3.4) of the sCRISP-A approach.

The orientation phase intends to give organization a direction for the use of Analytics. To gain competitive advantage, this direction depends on organizational characteristics that determine the competitive position or the intended future competitive position and the organizational strategy to achieve this position. As such, before planning and executing any Analytics action, this competitive position and the organizational strategy need to be analyzed in the **business analysis** task to ensure that Analytics strengthens them.

The subsequent task of **creating a strategic plan for Analytics** instructs the transfer of the previously analyzed organizational strategy into Analytics actions and initiatives, that support that strategy. Interviewees emphasized that building Analytics capabilities and applying Analytics is not and should not be a strategy in LSCM and most other domains but a tool to support the organizational strategies. Based on the identification of a plan that fits the organizational strategy, the required capabilities and technologies are determined as well as their investments. Further actions of this task enable the application of Analytics in a controlled and strategic manner, by allocating resources, promoting the topic and measuring its impact.

The task of **creating a foundation for Analytics** strongly depends on the identified requirements for Analytics. While all actions are likely to be relevant for organizations, the extent of their implementation differs by the determined support of Analytics to the organizational strategy. The scale of investments and provided training or the sharing agreements with partners depends on the chosen intensity of Analytics in the foreseeable future of the organization. However, in an economy with a growing role of data, actions regarding data quality, appreciative mindset towards use of data for decision-making and an established data governance are recommended albeit this planned intensity of Analytics. The value of data as an asset to the organization should not be neglected.

Eventually, **use cases** are required to realize the strategy and create returns on the investments in capabilities and technologies. The task lists several actions to identify use cases, which usually demand the support of employees with experience in Analytics. Thereby, interviewees expect that business units have a multitude of organizational issues at hand, they want to have resolved. Creating an Analytics use case from these issues still requires the formulation of a business problem, which is addressable with Analytics.

(1) Business analysis • Identification of value delivered to the customers, the applications used to drive the business (IT Systems, Management tools) and core business processes [incl. indirect value created from internal improvements].
(2) Creation of a strategic plan for Analytics • Identification of Analytics actions and initiatives supporting to the strategic objectives of the organization and derivation of foundation for strategy-ready Analytics. • Identification and support of thought leaders in Analytics (managers and business experts). • Allocation of Analysts (in centralized unit and decentralized in business processes). • Formulation of strategy to monitor impact and performance of Analytics.
(3) Creation of a foundation for Analytics • Investing in required technologies, systems and data architectures, their updates or replacements. • Creation of a data governance (responsibilities for data and data sources, transparency of data sources' existence and location, data access restrictions and policies, ethics and privacy code of conduct). • Implementation of data quality assurance processes and technologies (including datafication and automated data collection) and creation of appreciative mindset of data (use, collection, sharing, quality and critical reflection of usability). • Creation of data exchange agreements with partners. • Provision of Analytics tools, alignment of tools across organization and promotion of available tools. • Creation of data literacy and Analytics capabilities (trainings, education, demystification of buzzwords). • Creation of opportunities for communication and exchange between analysts.
(4) Use case identification • Observation of business unit's operations, decision-making, data collection and data usage by analysts to ideate potential use cases in coordination with business units. • Execution of analysts-supported ideation workshops for use cases in business units. • Stimulation of use case ideation in business units (presentations of successful use cases, inside conferences on Analytics, knowledge platforms). • Identification of upscaling potential of successful Analytics solutions. • Identification of unstandardized Analytics solutions ("Business owned tools") to standardize and upscale. • Identification of external use cases (including based on archetypes identified in section 4) transferable to the organization (and their potential improvements). • Regular reevaluation of use cases omitted due to unfitting data and technologies.

Table 8: Tasks of the orientation phase

7.3.3.2 Phase 1: Business understanding

The supplemented business understanding phase is divided in five tasks as presented in detail in Table 9, which ensure the initiative can create the aspired value. Interviewees stressed the fallacies of either loosing track of the objective of an initiative due to multiple strong and conflicting opinions of stakeholders or the development of Analytics solutions without any user in mind. In both cases, deployment and use of the Analytics solution is unlikely and no value is gained from the solution to compensate the investment. This phase ensures to develop an Analytics solution that solves a business problem, which has a problem owner able to participate in the development and is provided with fitting resources for the development. All tasks originally included in the CRISP-DM are adjusted and a specific stakeholder analysis task is also included in the sCRISP-A to emphasize the actions, which received little attention in the original approach.

The task of **determining the business objective** demands a clearly formulated and agreed problem statement, which is likely to initiate discussions. However, early discussions are beneficial as compared to discover a misalignment of understanding of the objective between stakeholders at a later stage. Further actions evaluate the relevance of the business problem to the organization and determination of success and failure criteria.

The actions of the task to **assess the situation** lead to an understanding of the environment the Analytics initiative will be executed in and the Analytics solution will be deployed in. Thus, a variety of information is collected about resources, requirements and assumptions as well as previous attempts to solve the business problem. The task concludes with estimations about the ability of solving the problem with the given resources and conditions. Further, an estimation of costs and benefits is conducted.

The **stakeholder analysis** task ensures the identification of relevant stakeholders and their expectations. Data presents the user of the Analytics solution as most relevant stakeholders. Adherence to their requirements is vital to ensure the use of deployed solutions. Stakeholders are further able to provide relevant information, funding, and elimination of obstacles such that their identification and updating them their scheduled, stakeholder-oriented and regular on the initiative's progress is important for the initiative.

During this phase of business understanding, repeatedly redefining the business objective is clearly intended to ensure the initiative develops an Analytics solution valuable to the organization and the intended users. In the task of **determining the Analytics objective**, this is supposed to be done implicitly. While executing the actions to determine the Analytics objective, the analysts evaluate the formulated business problem and the achievable business impact from a data analysis necessary to solve the business problem. Thus, analysts are obligated to point out identified mismatches between the analytical output and relevant value to the business process. This becomes especially relevant, if the Analytics objective is formulated by the business experts without formulating a business problem. As support for the analysts' assessment, they can use the results of preliminary exploratory data analysis and eventual prototyping.

Finally, this phase concludes with the task to **produce the project plan**, which includes a redefinition of the problem statement with increased accuracy and fit to the situation, the creation of the plan and the conclusion of a formal agreement on the initiatives content between stakeholders and analysts. Eventually, as indicated by the specific action, several of the actions must be repeated to close this agreement, which, however, is intended to ensure a smoother progress of the initiative.

(1) Determination of business objective

- Determination of initiative objectives from a business perspective, resolution of competing objectives, assessment of business need and impact of objective, and evaluation of objective's fit to organizational strategy.
- Evaluation of Analytics as best approach to achieve objective ("reality check").
- Determination of initial success and failure criteria of the Analytics initiative.
- Formulation of initial problem statement.

(2) Assessment of situation

- Identification of available resources (experts and skills, data, computing, software/tools).
- Identification of constraints and requirements (organizational control over process, process stability, flexibility and standardization, data security, privacy, legal aspects, required domain knowledge of analysts, analytics sophistication of customer).
- Identification of assumptions (users' intended use of solution in workflow or process, is problem solvable, is solution deployable).
- Research on previous solution attempts to the business problem (of organization and external, with and without Analytics).
- Obtaining definitions of organizational business language and key terms.
- Estimation and communication of deployment and maintenance effort.
- Estimation of costs, benefits and risks.

(3) Stakeholder analysis

- Identification of stakeholders interested, affected or benefitting from the initiative (including project sponsor and supply chain partners if relevant), their stake and interest in the initiative, and their expected activities during the initiative.
- Collection and systemization of various stakeholder perspectives on the problem statement, complexities and trade-offs in decision-making as well as solution requirements and (biased) expectations for the solution (especially the requirements and expectations of the intended user).
- Planning of stakeholder encouragement for participation and communication, and stakeholder management strategies (including identification of additional value-adding activities of stakeholders with reduced workload due to process automation); [depends on stakeholders' importance, inner circle of initiative with regular meetings might be created].

(4) Determination of Analytics objectives

- Determination of initiative objectives in technical terms and technical output of an Analytics solution to achieve business objectives
- Determination of initiative success and failure criteria in technical terms.
- Inventorization of available data, their assessment of fit to initiative objective and identification of data gaps requiring external procurement of data or adjustment of objectives (including postponement of some intended objectives until data become available).
- Formulation of ideas to test with the data based on data exploration, business expert interviews or prototyping.
- Assessment of needed analytical skills and expertise and comparison with available expertise.
- Communication of intended Analytics solution to stakeholder [according to stakeholder communication plan] (may include presentation of prototype to adjust and redefine business problem).

(5) Production of project plan • Formulation of redefined problem statement (increased accuracy, appropriate to stakeholders, fitting to available Analytics tools/methods, including possible alternative courses of action) • Institutionalization of cross-functional team (including business experts and decision makers, IT experts, analysts, data engineers). • Description of plan (steps, tools, timeline, designated team members, review points) to achieve technical objectives and resultingly business objectives. • Formulation of redefined success and failure criteria with metrics, which are negotiated, published, committed to, and their tracking planned. • Formulation of strategy to increase organizational visibility of the initiative. • Identification of authority with decision rights for situations of disagreement amongst project stakeholders or project team members. • Repetition of previous steps until permission to proceed with the initiative is granted by stakeholders. • Establishment of formal agreements (memorandum of understanding and letter of content) between Analysts unit and business unit (including purpose and objective as well as purpose of data sharing, privacy and data protection, assurance of transparency and commitment for each party involved).

Table 9: Tasks of the business understanding phase

7.3.3.3 Phase 2: Data understanding

The data understanding phase includes tasks that lead the team members, especially the analysts, to understand the data in a variety of dimensions. Besides the content of the data, understanding is created of the contexts of the data, the data sources and ways of accessing these sources, the specifications of tools and technologies needed to analyze the data, and the quality of the data. The tasks of this phase are detailed in Table 10.

The task of **collecting data and observing their usage and collection in the process** includes data assessment and acquisition actions. These already indicate potential trade-offs of data that are relevant to the analysis and the effort to get the data for the analysis. Hence, the needs must be prioritized. This requires understanding on the relevance of different data to the problem, which analysts must build prior to data collection by asking experts or observing data collection and use in the process. Interviewees recommended this field-and-forum approach multiple times due to its benefits to all analytical steps.

The subsequent **data description** task ensures the use of the right technologies and tools for the data. It includes several actions to ensure the Analytics solution will be deployable, since access to data for deployed solution is understood and attention for relevant data accessibility issues can be raised at an early stage in order to solve them in parallel to data analysis. Interviewees further recommended containerization of the sandbox environment such that it resembles the deployment environment and simplifies deployment.

The third and fourth tasks could be interchanged since they both represent tasks potentially uncovering unsolvable obstacles for the Analytics initiative but are not dependent on each other. However, the observed convention is to **explore the data** first.

Actions of this task include pattern and relationship detection and their communication to stakeholders to discuss potential adjustments of the initiative's objectives.

Fourth, **data quality is assessed**, and cleaning strategies are decided, which should primarily be justified by business and process relevance. Steps to transform data by filtering and cleaning are automated at this point. However, the next phase will focus on applying the cleaning techniques and prepare data for analysis. This third phase demands precise documentation of decisions and their justification to allow recreation of decisions later on as well as allow reusability of applied data integration and transformations.

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(1) Collection of initial data and observation of data handling in the process

- Identification of data needs from problem statement and business understanding phase and examination of existent organizational data (structured and unstructured).
- Inquiry of business and process experts for potentially relevant critical internal and external effects to decision-making.
- Field (and forum) observation of the data collection and data usage in the decision-making by the analyst to understand meaning of data, original context of data, sources of variation and their categorization (controllable/not controllable), and the eventual impact of an Analytics solution as support to decision-making.
- Critical reflection of use of data and potential Analytics solution output in the decision-making and recommendation of adjustments.
- Prioritization of required data and identification of best way to acquire or access the data.
- Acquisition and/or collection of data (including conviction of data owners and set-up of new data collection if necessary).
- Recording of encountered problems with data acquisition and collection and their resolutions.

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(2) Description of data

- Documentation of physical locations of data collection, their accessibility, required tools and infrastructure needed to handle data, and evaluation of the data integrity in the source the data is extracted from as well as evaluation of the ability to automate data extraction.
- Preparation of the Analytics sandbox environment according to documented requirements and evaluation and loading of initial data into sandbox environment.
- Surface examination of data characteristics, review of fit to requirements, and identification of potential issues.
- Filtering of relevant data and structuring (creation of meta data, tagging)
- Examination and inventorization of data and data sources to build understanding on availability of data, accessibility of data sources, additional data collection needs, and data acquisition needs from third parties.

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(3) Exploration of data

- Application of explorative techniques (queries, visualizations, reporting techniques, search of patterns, trends, relationships and anomalies including documentation of them being anticipated or unanticipated).
- Identification of performance measurement of existing decision-making process from data as basis of comparison (if relevant and possible)
- Documentation of initial insights, initial hypothesis, recommended levels for parameters for analytical models, and identified needs for data preparation
- Redefinition of business problem statement/business objective and Analytics objective based on data exploration results,
- Determination of reporting and documentation strategy for different stakeholders and communication of exploratory data analysis results and recommended objective redefinition [according to stakeholder communication plan (e.g., presentation in regular meeting)].
- Creation of identified side products relevant to stakeholders and users (dashboards, scoreboards), if requested based on reported result of data exploration.

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(4) Verification of data quality • Examination of data quality, documentation of quality issues, and identification of data cleaning strategies. • Evaluation of cleaning strategies with business experts. • Design and set-up of Extract-Transform-Load process based on agreed data cleaning strategy. • Documentation of used data cleaning strategies and their business knowledge supported justification. • Reevaluation of business and Analytics objectives based on severity of data quality issues jointly by analysts and stakeholders.

Table 10: Tasks of the data understanding phase

7.3.3.4 Phase 3: Data preparation

While only few actions are listed for the tasks of the data preparation phase, these actions can be cumbersome and time intense. Several tasks may be revisited and repeated if the analysis methods are changed or adjusted in the course of the analysis phase since the actions of phase 3 are highly dependent on the analysis method. The tasks, which are detailed in Table 11, show some similarity with the tasks in the data understanding phase, but while the previous phase focuses on getting access to data for analysis purposes, this phase prepares the data for a specific analysis prioritized in the business understanding phase and experiences made in iterations of the modeling phase.

The **cleaning** task includes data cleaning actions as decided in the previous phase to a data set chosen for the analysis. This could be a sample of the initial data set chosen by timeframe, included internal and external factors, random choice or other criteria. The impact of cleaning is documented for the purpose of replicability but could already benefit the initiative, if it must be repeated for another sample. The impact is further assessed.

While raw data does not necessarily have features with the relevant information, level of aggregation or explicit effect required for the analysis, features must be **constructed** from it. Resultingly, the construction of data task includes actions to create these features, which have more powerful impact in the analysis methods as opposed to the raw data.

Subsequently, the task of **integration** is necessary since data in more complex analysis rarely are collected from one single source. Hence, the data must be merged, which demands the identification of equal identifiers in the data sets from the different sources. This task is usually complicated by historically grown or heterogenic data sources never intended to be integrated. Thus, achieving matches can become very time intense.

Finally, further actions that adapt the data to analysis methods without changing their meaning are performed in the **formatting** task. This task may not only depend on the intended analysis method but also the combination of features with disparate scales. After all actions are performed, analysts are able to evaluate the usefulness of data. Thus, an additional evaluation is performed and documented for later reference.

(1) Cleaning of data • Execution of data cleaning strategies, documentation of them and evaluation of their impact.
(2) Construction of data • Identification of features for data analysis to achieve business objective. • Creation of features from the data with required attributes for analysis from collected and available data.
(3) Integration of data • Merging and aggregation of the data relevant for subsequent analysis.
(4) Formatting of data • Execution of syntactic changes to the data, which keep the meaning of the data but are necessary for the modeling (harmonization, standardizing/normalization, rescaling). • Categorization of data by usefulness and documentation.

Table 11: Tasks of the data preparation phase

7.3.3.5 Phase 4: Modeling

Comparable to the previous phase, the modeling phase includes several tasks with few actions creating a perception of minor effort as presented in detail in Table 12, while the extent and expectable repetition of tasks leads to extensive effort and time consumption. In the sCRISP-A, the expected repetition of tasks is emphasized and established due to the iterations described in the tasks. Interviewees clearly recommended to execute these iterations in a format oriented on agile project management. Another major adjustment is the included set-up task, which establishes a working environment intended to overcome issues quickly and goal-oriented and enhance collaborative work.

As explained above, the **set-up** task includes actions to advance collaboration, especially of analysts and users. Thus, a tool or procedure for collaboration must be established, which can be used to present and discuss intermediate solutions/prototypes, and fits either expertise. Interviewees mentioned Tableau or Shiny as examples, but several alternatives exist. Further advanced collaboration depends on the complexity of the initiative.

In the **selection** task, operationalization of an analytical method is initiated by selecting a specific modeling technique or algorithm. Depending on the performance and adherence to the business problem’s success criteria of the selected technique or algorithm, this task must be revisited, and another technique or algorithm chosen. It was particularly stressed, that the technique and algorithm should be chosen by relevance and not by popularity.

The task of **generating a test design** is dependent on the specifically chosen modeling technique or algorithm and demands additional preparation steps on the data. Commonly, training, test and validation sets are created, which allow to test the results.

Subsequently, techniques are applied and assessed in agile cycles. The **building** tasks may create several models with low performance, which can be recognized for insufficiency to the business objective. In this phase, the documentation of adjustments taken is critical to avoid redundant tests. Sufficiently performing models and applied algorithms are taken to the next task.

Finally, the **assessment** task includes a variety of assessments according to relevant criteria to the modeling technique and the business problem. Discussing the results with users or process experts is shortly mentioned in the CRISP-DM but strongly emphasized in more recent approaches, the interviews, and the results of this thesis. In this sense, presentable and discussable products (intermediate solutions, prototypes) are supposed to be created, which are used as reference for discussion to identify the residual to users' expectations and requirements and to give analysts the opportunity to show issues in a comprehensible manner. This discussion is the basis for the decision to proceed with the solution or to readjust it in further iterations. A deviation of the activities in the Analytics initiatives from the agreed business objective was expressed as being particularly likely in this phase due to individual stakeholder opinions expressed as reaction to results. Thus, this task includes an evaluation of the adherence to the business objective.

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(1) Set-up

- Establishment of a tool for simplified and advanced collaboration and exchange between analysts and users or process experts (should make results consumable to users and process experts and not involve review of programming code [e.g., process diagrams, visualization, performance indicators]).
- If business problem requires, co-location of Analysts with intended users or process experts for short feedback cycles.
- If business problem requires, identification of further analysts in the organization, familiar with similar business objectives and the chosen analysis method to establish exchange between analysts on demand.

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(2) Selection of modeling techniques

- In agile iterations, selection of specific modeling technique/algorithm and their parameters based on the chosen analysis methods, and their documentation (including assumptions, considerations on the deployment environment and ability to explain to users).
- Selection of statistical software package/package of programming language to apply modeling technique/algorithm.
- Communication of chosen technique to stakeholders including their pros and cons [according to stakeholder communication plan].

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(3) Generation of test design

- Planning of procedure to test quality of the model/applied algorithm and preparation of data accordingly (such as building of training and test set).

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(4) Building of model/application of algorithm

- In agile iterations, application of modeling tools and algorithms to create and refine models based on criteria evaluation fitting to the solution of the business objective and adhering to cost and time constraints.
- Documentation of adjustments, issues and decisions on modeling technique and algorithms [(e.g., using git version-control systems)].

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(5) Assessment of models and algorithm applications • Interpretation and evaluation of created model/applied algorithm regarding methodological criteria (modeling success criteria, test design, sensitivity analysis/what-if analysis of parameters). • Evaluation of plausibility of model/applied algorithm, assessment of adherence of model/applied algorithm to intended deployment environment and usage, and application of retrospective test (evaluation of model/algorithm performance on historical data). • Documentation of assessment and validation process (including ranking of models/algorithm applications accounted to methodological criteria and business objective). • Extraction of results as information and visualizations (patterns, discovered insights, visualizations) and creation of intermediate solution/prototype/minimal viable product presentable to stakeholders. • Discussion of intermediate solution/prototype cross-functionally (at least, analysts with users or process experts) to identify missed requirements and expectations, to close knowledge gaps on potential improvements, to determine issues with the solutions and missing resources or data and convert interpretations into actionable insights for the organization. Discussion should emphasize addressed improvement potential identified in previous iteration. • Evaluation of adherence of activities of Analytics initiative to business objective (extensive stakeholder input can divert actions from agreed objective). • On "satisficing" solution ("good enough" for the users for the problem at hand), continuation to next phase or, otherwise, initiation of next iteration (revisit building task) with eventually changed analysis method (revisit selection task).

Table 12: Tasks of the modeling phase

7.3.3.6 Phase 5: Evaluation

After a time-consuming development of an Analytics solution, either as discovery or as software product, the evaluation of the value and usability of the solution development process is conducted as presented in detail in Table 13. Any developed solution not passing this phase will not create value to compensate the investment and effort. However, the data collected for this thesis illustrates failed deployment of potentially valuable solutions due to failed evaluation phases, which did not clarify the value of the solutions, did not allocate the necessary steps and responsibilities to deploy the solution and did not enforce a decision on subsequent steps with the solution. Thus, the sCRISP-A extends the solution presentation and its preparation to separate tasks to underline the importance and provide directions for a more goal-oriented solution presentation.

While the previous phase created a model or applied algorithm in a laboratory environment, the performance of that solution must be tested in the real process – the so-called production environment. In the **evaluation of results** task, a pilot solution is created and field tested in the production environment. This test provides relevant information of the value the solution can generate in the process.

Before presenting the solution to stakeholders, which represents a commitment of the team to correctness of the solution, the process is **reviewed**. Thereby, the team benefits from detailed and complete documentation, which diverts time from advancing the Analytics solution during the development but supports the team to recreate their steps.

Following the indications above, the **preparation** task for the communication of results was included in the sCRISP-A to reserve time to identify communication strategies and create an impactful solution presentation. The focus of the actions of this task is to create a solution presentation, which convinces the users (and other stakeholders) from the value of the solution. Convincing the users is a crucial contribution to motivate them to use the solution in the process, even if the solution demands changes of the users' work and processes or the implementation has a bumpy ramp-up.

Finally, the solution is **presented**. The actions of this task anticipate some issues such as stakeholders reluctant to commit to subsequent steps, decisions on further steps without allocating tasks and responsibilities, or stakeholders trying to expand the initiative with additional objectives (without increasing resources and budget). As good project management measure and in line with the suggested agile project management methods, a retrospective is recommended at the end of this phase.

(1) Evaluation of results • Assessment of model's or applied algorithm's adherence to business objectives. • Development of field tests/pilot studies including performance criteria. • Execution of field tests/pilot studies and examination of technical requirements. • Summarization of model evaluation in business success or failure criteria of the initiative including evaluation of usefulness for the business process.
(2) Review of process • Assurance of process quality by reviewing and eventually repeating activities.
(3) Preparation of communication of results • Determination of the communication strategies of the results to the stakeholders in addition to solution presentation. • Identification of relevant talking points for solution presentation besides solution pilot (surprises, established success and failure criteria, validated ideas/hypotheses, most significant findings, assumptions, limitations, accuracy, caveats). • Projection of planned subsequent steps and responsibilities of team members, stakeholders and other business units/teams. • Orientation of solution presentation towards ensured consumability for intended users (use of business terms, solution evaluation in business value, emphasis of relevant input from users to the development of the solution, expected process changes and its ramp-op with adjustments to the solution).
(4) Presentation of solution and determination of next steps • Presentation of [/workshop on] solution and results with stakeholders (including users). • Emphasis on the need for further action by stakeholders to generate value from the solution and insights. • Decision on subsequent steps and documentation of reasoning (realization of planned steps of the team members and moving to deployment phase, initiating another iteration to adjust solution, initiating a subsequent Analytics initiative to further advance the solution, halting the Analytics initiative). • Documentation of newly raised business questions stimulated by the presented solution, which can be addressed in subsequent Analytics initiatives. • Collection of recommendations for future Analytics initiatives based on learnings and encountered obstacles.

Table 13: Tasks of the evaluation phase

7.3.3.7 Phase 6: Deployment

After the approval of the Analytics solution, it must be deployed. The deployment phase finishes the development of the Analytics solution, which marks the final phase in the original CRISP-DM. Thereby, either a software product is finalized and implemented into the IT eco-system ("Analytics product" or "data product") or a discovery is provided to management to initiate organizational changes. The investigated approaches to manage Analytics initiatives and the interviewees primarily focused on the former such that users are provided with a decision-support tool or some process automating capability. The latter has a significantly shorter deployment regarding the Analytics initiative, since the product to transfer the discoveries is usually a PowerPoint slide deck or a report. These reports demand subsequent projects based on the discoveries to create organizational changes exploiting the discoveries. The tasks of the deployment phase are presented in detail in Table 14 with actions primarily focused towards Analytics products.

Across the investigated approaches, the deployment phase is implicitly understood to require an additional team of software developers for programming and implementation of an Analytics product. Thus, the actions of the Analytics initiative's team members are limited to **preparing the solution** for these software developers and preparing the users for using the solution. In contrast to the original CRISP-DM, a very explicit and strong focus is put on the users and their expected handling of the solution in the sCRISP-A.

The performance of deployed Analytics solutions is influenced by a variety of factors. Internal factors can limit the impact and functionality of solutions such as users using the solution in the wrong way or changing IT landscapes compromising data inputs to the solution. External factors such as changing market conditions or changing customer behavior including changed behavior due to deployed solutions can result in reduced validity of solutions. In both cases, the quality degradation of solutions must be detected and countered. To enable longevity and durability of solutions, **maintenance and monitoring is planned**. To improve understanding of the impact of Analytics solutions on the organization, which can eventually be used as motivation for further initiatives, a long-term evaluation of the business value is additionally planned.

While a multitude of documentations and reports is created along the Analytics initiative, the task of **producing a final report** is supposed to collect information beyond justification and reproducibility of actions. The team is asked to look ahead and consider scalability, changes in the organizational knowledge and the opportunity to spread the message on the solutions success across the organization. Actions of presenting the value and benefits of created solution is extensively incorporated into the sCRISP-A. The idea behind this communication is not to increase the popularity of Analytics per se but present a tool to the organization, which has achieved beneficial outcome and could potentially create further benefits, and is thus in the best interest of the organization.

Finally, the deployment phase closes with a **review of the project** by the team members, which are likely to participate in future Analytics initiatives. This review is more focused on operational topics not discussed with or rather not relevant to stakeholders in the evaluation phase's review. However, the insights from the review with the stakeholders can be incorporated. This task should produce a formal document of recommendations.

(1) Planning and preparing of deployment • Adjustment of solution to deployment in process (recommended courses of action are explicit to the users, integration of Analytics solution into workflow of users fits their decision-making, decision support and recommendations from the Analytics solution are quickly comprehensible to the users, enabled level of self-service and drill-down capabilities fits users process) • Identify additional data collection points to record decision-making of solution supported process. • Determination of deployment strategy, the necessary steps and their execution. • Initiate deployment and integration into existing systems. • Testing of deployed solution by executing a peer review for technical correctness and evaluating the accurate transformation from developed model to production environment as well as resolving issues. • Development and provision of training and training material (documentation, seminars, videos) and initiation of change management to build understanding, acceptance and incentivize use. • Explicit communication to the user on the responsibility to consider insights from the Analytics solution for their decision-making. • If relevant due to solution complexity or process characteristics, introduction of Analytics solution gradually into the process of users, benchmarking of performance of process with and without Analytics solution and testing of solution's correctness.
(2) Planning of monitoring and maintenance • Determination of maintenance strategy (including evaluation of correct usage of Analytics solution and improvements/adjustments over time) • Implementation of monitoring process of deployment (determination of performance measurement criteria over time, bounds of operation and performance levels triggering alerts, responsible teams and key stakeholders needed to be informed). • Scheduling of long-term evaluation of business value. • Documentation of maintenance and monitoring.
(3) Production of final report • Creation of report about project, experience, and results. • Summarization of derived insights and their conflicts to existing knowledge. • Recommendation of opportunities to scale solution to further processes (in adapted form). • Planning of measures to create broad visibility of Analytics solution success, value and benefits in the organization. • Execution of concluding presentation for stakeholders.
(4) Review of project • Final assessment of the project (positives, negatives, improvement potentials).

Table 14: Tasks of the deployment phase

7.3.3.8 Phase 6+: Support

Finally, the support phase follows the development of the Analytics solution and ensures the exploitation of the maximum value and benefits from solutions as presented in detail in Table 15. This phase maximizes the long-term return on investments of Analytics solutions in production that finally create value compensating their investments (and the maintenance effort). It further creates spillover effects to other Analytics initiatives by ensuring the distribution of gained knowledge during the Analytics initiative.

The task of **evaluating the usage** of the Analytics solution is primarily the responsibility of the users themselves since the development team has separated in this phase. Users are demanded to actively reflect their usage of the solution and collect feedback on necessary changes and improvements. They must further communicate their need for re-training to Analytics experts to obtain the best support for their processes. Depending on the users' role, these responsibilities might be exercised by users' supervision or management.

In parallel, the task of **distributing the documentations** from the initiatives is executed. The responsibility of this task is assumed by Analytics experts but not necessarily by the development team members. Actions of this tasks lead to the distribution of knowledge as passively being available at easily accessible places or as actively provided trainings to analysts or other roles potentially participating in Analytics initiatives.

Lastly, **monitoring and maintenance** are conducted. The actions require Analytics experts to be involved. Experts with knowledge on the solutions are particularly valuable contributors and reactivating former development team members can enhance the impact of methodological or technological advancements. However, maintenance addresses minor solutions adjustments to recent changes in data or users' feedback. Major changes should trigger novel Analytics initiatives with individual value to compensate efforts. To conclude, the necessity of gaining business value and benefits from applying the tool of Analytics equivalently upholds for improvements of Analytics solutions.

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(1) Evaluation of usage

- Users assume responsibility of the Analytics solution (assurance of solution's use in the process, management of solution, formulation of requests for advancements)
- Tracking of decision-making in the Analytics solution supported process and the conformity to the solutions recommendations.
- Collection of user feedback (perceived performance, usability, consumability of decision support, speed, scope of capabilities, and need for adjustments to changes in process, organization, or industry).
- Provision for regular re-education on Analytics solutions functionality and use of results, and opportunities to ask questions (short trainings, webcasts).

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(2) Distribution of documentations • Provision of created documentations at (redundant) places that ensure accessibility of relevant information (used and integrated data sources, methods used to clean and harmonize data, Analytics problems and applied modeling techniques/algorithms, recommendations for future Analytics initiatives, and identified use cases and scaling potential of developed solution). • Creation or advancement of trainings for analysts based on knowledge generated in Analytics initiative (applied modeling techniques/algorithms, recommendations for future Analytics initiatives)
(3) Application of monitoring and maintenance • Regular analysis of performance of Analytics solution (adherence to evaluation criteria and quality parameters, validity of data sources, need to adapt solution to new data, need to adapt solution to altered business problem, [need for re-training of machine learning models]). • Identification of technical improvement potential for Analytics solution (improved modeling techniques/algorithms, improved packages to apply modeling techniques/algorithms, improved technologies to host and operate solution) • Tracking of indicators of business benefit and assessment of business impact of the Analytics solution with eventual simulation of organizational behavior without solution (created savings, increased profit, increased return on assets). • Application of necessary adjustments to Analytics solution (implementation of users' feedback, countering measures to performance degradation, initiation of Analytics initiative to advance modeling technique/algorithm or foundational technology, initiation of Analytics initiative to transfer solution to other processes)

Table 15: Tasks of support phase

7.3.4 Case study-based evaluation of approach to manage Supply Chain Analytics initiatives

To critically reflect and validate the sCRISP-A, it has been examined based on a case study of a running Analytics initiative. The Analytics initiative of the case study intends to provide a predictive Analytics solution in a cross-organizational LSCM process. The case study is primarily focused on conducting a feasibility study and developing a prototype of the solution. At the moment of examination, the initiative is in the modeling phase. Resulting from this circumstance, the case study representative has been asked to evaluate the phases following the modeling phase based on professional experience and experience from the initiative.

Regarding the orientation phase, the focal organization of the case study initiative has been described to be aware of value drivers to the customer. However, in line with the results of this research, the case study initiative is also oriented on internal process improvements with indirect value for the customer instead of customer facing solutions. Since this has not been emphasized but implied in the sCRISP-A, it was included afterwards. Further, the focal organization was described to have fundamental building blocks of a strategic plan for Analytics and moderate foundation for Analytics, which has been supportive to the case study initiative, but does not remove all obstacles. Resultingly, use case identification was perceived as isolated process in business units instead of systematically applied across the organization. Thus, especially the accessibility of data owners and their data as well as the oversight on Analytics activities across the organization was experienced as inadequate. Hence, the proposed orientation phase has been endorsed by the case study representative since it would resolve issues experienced in the case study initiative.

The business understanding phase of the case study initiative has been an already identified weakness by the representative. The Analytics objective of the initiative had been agreed upon without a clear problem statement. This resulted in challenges in defining requirements on the solution or the characteristics of the solution, as well as to identify needed data and skills. Further, tasks could have been executed more efficiently and in shorter time with a clear problem statement. Thus, starting an initiative with the determination of the business objective has been endorsed by the case study representative. Further, due to the cross-organizational nature of the initiative, the formal agreement had been concluded before an assessment of the situation, stakeholder analysis or initial assessment of available data had been conducted. Thus, the agreement did not fit to the best approach to the initiatives but required the execution of tasks barely contributing to the solution. Resultingly, the case study representative endorsed to conclude the formal agreement on project plan and tasks to the end of the business understanding phase. Further tasks in the initiative were conducted in the sequence as recommended in the sCRISP-A and the sequence was confirmed as proper. Regarding specific tasks, the case study representative emphasized the stakeholder communication as being dependent on the stakeholder importance with the most important stakeholders being present in regular meetings. These meetings were described to provide a platform for all the communication activities listed subsequently in the sCRISP-A. In addition, defining the Analytics objective includes the investigation of possible analytical methods to address the business problem. While this does not indicate the choice of specific techniques, it might include ideas and thoughts on combinations and chaining of techniques representing analytical methods. These comments have been included in the sCRISP-A.

In the discussion of the data understanding phase, the case study representative agreed completely to the comprehensiveness and sequence of recommended tasks. Especially the cross-functional cooperation, which is emphasized in the sCRISP-A, was endorsed such as the field and forum observation of the process by analysts to gain deep understanding of the process, and the involvement of business experts in solving data quality issues. This form of cooperation was explained as being vital for goal-oriented development of Analytics solutions.

Similar to the prior phase, the tasks and activities of the data preparation phase were acknowledged as comprehensive and correct in their sequence. The case study representative explained that this phase remained uncompleted and ran in parallel to the modeling phase for some time. Due to the cross-organizational initiative, stakeholders of organizations, which had already provided data, demanded to see prototypes while other were still working on providing the data. However, the indication of a loop of these phases included in the sCRISP-A was deemed sufficient to represent such eventual abnormal behavior.

Regarding the modeling phase, the inclusion of the set-up task in the sCRISP-A was endorsed. Prior to any modeling in the case study initiative, modes of communication were created. Driven by the analysts, process diagrams of the analysis including input and output as well as visualizations were created aiming at consumability of the results to the users and reusability along different modeling techniques. Further, in cooperation with stakeholders, the analytical performance indicators for the modeling phase were specified. The benefits of setting up these communication products before applying modeling techniques have been goal-orientation and a clearer benchmarking of progress. For documentation purpose, modern git version-control applications have been suggested by the case study representative since they were appropriate to the case study so far. The use of agile project management methods was discussed and while these methods were recommended as supportive, it was clearly explained that scrum sprints were not possible due to other responsibilities of the team members of the initiative. The iterative development of intermediate solutions was instead denoted as “rapid prototyping”. However, this acknowledges the development of intermediate solutions which are discussed with users and business experts to identify residuals to requirements, solutions for issues and improvement potentials as already included in the sCRISP-A.

The tasks of the evaluation phase have been acknowledged in comprehension and sequence by the case study representative. Thereby, the specifically emphasized user orientation of the solution presentation in the sCRISP-A was endorsed by the case study representative. As a comment on the solution presentation task, the presentation in the described complexity was recommended to be elevated to an extensive workshop if all described activities are supposed to be executed. It was further underlined that this might be the last chance to discuss the solution, subsequent steps and learnings with all stakeholders since it might be perceived as conclusion of the initiative even though the deployment phase follows this phase. However, the phase only concludes the solution development.

As for the evaluation phase, the tasks of the deployment phase have been evaluated based on the professional experience of the case study representative and the experience with the case study initiatives with a resulting anticipation of which tasks and actions would be necessary. Since the case study initiative has not been concluded, this anticipation format was necessary. The tasks, actions and their sequence in the sCRISP-A have been acknowledged. It was discussed that a data collection on made decisions from an eventual Analytics solution might be too complex to implement. In the case study initiative, this would be certainly the case due to the cross-organizational nature.

Finally, the evaluation stage introduced in the sCRISP-A was endorsed by the case study representative. While the idea of giving the responsibility of the solution to the users was confusing in the beginning since they do not have the skills to perform monitoring and maintenance, this confusion was resolved after the range of tasks and activities was explained including the allocation of responsibilities to Analytics business units. Since the case study initiative is focused on machine learning techniques, the explicit inclusion of their re-training was suggested. Beyond that, no issues were raised.

Summarized, the sCRISP-A was acknowledged for comprehensiveness and appropriate sequence of tasks. Proposed phases and tasks, which were not included in the original CRISP-DM approach were endorsed for their relevance. After the adjustments resulting from this case study-based examination have been applied to the sCRISP-A, it is considered as validated.

8 Conclusion

This thesis has investigated the management of Supply Chain Analytics (SCA). For this purpose, the thesis is structured by the five stage strategy execution process (SEP) by Gamble et al. (2015). For stage 1 of the SEP, a vision, mission and values for this thesis have been formulated. Resultingly, this thesis envisions a state of LSCM organizations being enabled to achieve sustainable competitive advantage and continuous improvement from SCA and aspires to contribute to provide *guidance* that leads LSCM organizations towards this vision by conducting valid and reliable empirical research. For stage 2, individual objectives to fulfill this mission were derived. These objectives are oriented on the theory on structuring problems (TSP) from Simon (1973). The derived objectives advance the creation of a structure of the "problem" of a LSCM organization achieving to execute Analytics in the sense of the vision of this thesis. For stage 3, four research designs have been developed to achieve the objectives. These research designs have been realized by rigorous empirical research employing a diversity of research methods. Thus, the following steps have been taken for each individual research design: elaboration of extensive theoretical background related to the research objective, collection of data and analysis of the data strictly adhering to methodological standards of an appropriate research methodology, and interpretation and discussion of results. The execution of the research designs is documented in four research articles, which form the body of this thesis. The final 5th stage of the applied SEP demands evaluation and analysis of factors, which suggest corrective adjustments. The evaluation is presented by the discussions on trustworthiness, implications and limitations individually included in the four articles as well as in the discussion on the scope of the thesis. Since the mission of this thesis is of providing *guidance*, two measures have been chosen as corrective actions to convert the results of the articles into guidance. First, several forms of value creation for customers through SCA were discussed. Second, an approach to manage Analytics has been developed by supplementing the popular CRISP-DM approach. The CRISP-DM approach has been compared to 14 (mostly more recently published) approaches and the insights on managing SCA generated in this thesis, supplemented accordingly, and validated by a case study. These two measures of guidance stimulate use case identification and design and execution of Analytics initiatives. This guidance is founded on the established notion in this thesis of Analytics being a novel tool for organizations. As such, it should be mindfully employed by comparing its potential to other tools in an organization’s toolbox and its cost efficiency in solving the organizational problem. This tool requires human expertise and creativity to identify valuable business problems and design Analytics initiatives to develop valuable solution. Hence, the guidance provided in this thesis emphasizes the importance of the individuals in organizations and their contribution to Analytics. Resultingly, it supports the exploitation of this tool by individuals to support individuals in their decisions and actions, because, as explained by an interviewee, “when data insights and [professional] experience come together, that's unbeatable”.

This section summarizes this thesis, presents limitations and gives an outlook on future research. The thesis is concluded by this section.

8.1 Summary

The motivation of this thesis is based on theoretical and practical aspects of the application of Analytics in the domain of LSCM. From a theoretical perspective, LSCM is an eligible domain to use Analytics due to its complexity and uncertainty and the data-intense decision-making. Technological and methodological advancements further make the use of Analytics accessible to LSCM. Scholars have presented the impact of exploiting SCA and the potential performance increases in LSCM processes due to increased visibility and reduced costs. Further, competitive advantages have been argued for the application of SCA in efficiency, innovativeness and quality. However, LSCM organizations are unable to realize these benefits due to encountered barriers.

Practically, the application of SCA is motivated by a variety of reported efficiency gains such as improved reaction time and increased product availability. Additionally, organizations exploit new business potential in new business models or new revenue streams. Central to LSCM, the customer orientation can be strengthened by improved understanding of the customers’ needs and increased achieved satisfaction levels. However, despite some organization gaining value from SCA, on average the LSCM organizations show reluctance towards it and give it a low priority, since they considered it as a “trend to pass by” or irrelevant to their business. Theoretical barriers and reluctance result in unused potential of resource-saving efficiency and service quality as well as it makes organizations vulnerable to new competitors in the market. This motivates this thesis.

The theoretical background of this thesis aligns the terms Logistics and Supply Chain Management, compares Analytics to Data Science, Big Data and Artificial Intelligence, and provides an overview of different domains applying Analytics. Given the extensive and clear similarities of the terms Logistics and Supply Chain Management and the lack of value for this thesis in distinguishing the terms, they are fairly treated as one term. LSCM represents the processes that enable the flow of materials and related assets, information and funds from the initial supplier to the final customer by actions of planning, controlling, executing and monitoring. It is ideally executed with holistic thinking and customer orientation.

Comparing the analytical terms of contemporary most relevance for this thesis, they overlap extensively but show nuances of individuality. Creating new terms for the analytical field is rooted to some degree in an advertisement of advancements, while final products and services sold under the newer terms may not necessarily incorporate the advancements. The term Analytics has been chosen as central term for this thesis due to its focus on management, while for the realm of management issues all terms are considered as synonyms. Analytics represents evidence-based problem recognition and solving within a business context, with evidence primarily referring to data. Regarding the incorporation of analytical methods into business, it is the most mature term of the compared terms. Due to its emergence during the domestication of analytical methods from analytical experts to non-experts in organizations, it has a dense consideration of management issues in the literature. In contrast, Big Data emerged with advancements in database technology, Data Science arose from advanced analytical methods, and the business popularity of AI follows from novel analytical solutions. These advancements in technologies, methods and solutions have usually little focus on management.

To emphasize the influence of the domain on Analytics, the application of Analytics has been presented for LSCM, marketing, healthcare, the public sector and sports. All fields show different use cases, different objectives in the application of Analytics and barriers arising from different characteristics of the domains. However, similarities are recognizable and Analytics itself shows a transferability to a multitude of domains. In this sense, while use cases may not be transferable with simple adaption of methods, the ideas behind the use cases could be transferred to enabled additional potential.

The first article ("Mapping Domain characteristics influencing Analytics Initiatives - The example of Supply Chain Analytics") explores differences of applying Analytics in

LSCM as opposed to other domains. The research develops a framework mapping a variety of potentially differentiating characteristics and influences among characteristics. LSCM displays a stronger focus on efficiency, descriptive and prescriptive use cases, and the use of mobile sensors. The domain is less knowledgeable on Analytics and the lifecycle of Analytics initiatives creating an entry barrier. LSCM perceives unfavorable conditions of less pressure by external forces to apply Analytics (e.g., regulations, requirements of customers), and many use cases demanding cooperation across organizational boundaries, which require a stronger persuasion for the potential of Analytics. The article uses and rigorously adheres to the Grounded Theory methodology building on twelve interviews. Its results contribute to later articles, the discussion on creating value for customers and the approach to manage SCA initiatives.

The second article ("Archetypes of Supply Chain Analytics") investigates the current state of SCA. In this article, six archetypes of SCA initiatives have been developed and labeled educating, observing, alerting, advancing, refining and investigating, with the labels referring to core objectives of these archetypes. The archetypes are based on 46 secondary case studies of organizations applying Analytics to LSCM, which were asymmetrically binary coded on 34 characteristics and hierarchically clustered with Ward's method. By interpretation of content similarities of case studies in the same clusters and dissimilarities between clusters, the cluster labels and descriptions have been developed representing archetypes of SCA. The results contribute extensively to the discussion of the value SCA can create for customers and minorly to the supplemented approach to manage SCA.

Article number three ("Explaining the Competitive Advantage generated from Analytics with Knowledge-based view") focusses on the condition of competitive advantage. It creates a well-argued explanation of critical practices for Analytics in the context of LSCM to create value – theoretical competitive advantage – from SCA. This article's results establish the problem-orientation of Analytics, the life-cycle view on Analytics solutions, the essentiality of steady cross-functional cooperation, and the understanding of Analytics as tool instead of a pillar of organizational culture (at least in LSCM), which strongly shapes the guidance this thesis provides. The provided explanation is based on the argumentation of the KBV for creating competitive advantage from integrating knowledge in the value creation process and reported practices and processes to gain value from Analytics. Derived testable propositions of Analytics best practices and their reasoning for being best fitting the theoretical argumentation of competitive advantage of the KBV have been tested with a multiple case study approach. Four case studies were collected from LSCM organizations and four from organizations providing Analytics to LSCM organizations. Thereby, each case study represented an individual experiment rejecting or supporting each individual proposition, which were subsequently aggregated. Compared to usual confirmatory research designs, this confirmatory design provided the unusually extensive explanations and information necessary to understand the creation of competitive advantage from Analytics. The results contributed extensively to the supplemented approach to manage SCA initiatives and minorly to the discussion on value for the customer.

Concluding the articles, the fourth article ("Overcoming Barriers in Supply Chain Analytics") explores measures LSCM organizations use to overcome barriers in SCA. Core themes of barriers and measures are presented including the effect of barriers on different phases of SCA initiatives and the impact of measures on barriers. Thereby, the individual barriers are described as well as several specific examples of measures given, while the research did not allow to implicate specific measures to overcome specific barriers due to the dynamically changing nature of measures and the dependence of effects on context and the development path. The measures provided are intended to stimulate ideas. To identify barriers and measures and to derive core themes, 13 experts in SCA were interviewed and data analysis was conducted based on a mixed methods approach using Grounded Theory and the Q-Methodology. The results of this article contributed extensively to the supplemented approach to manage SCA initiatives.

The value for customers from SCA was discussed based on data collected for the articles as first form of guidance to LSCM managers. The value organizations create must be distinguished in direct value for customers from LSCM organizations employing Analytics solutions for them and indirect value for customers from Analytics solutions focused on organizational improvements. LSCM organizations were identified to contemporarily focus their time and resources primarily on the latter due to the beneficial opportunities. Still, a non-exhaustive list of value for customers was presented supported by examples. The presented types of indirect value are increased reliability, increased service quality, and reduced costs. Direct types of value for the customer include improved operational efficiency, reduced time and increased availability of products and services.

Finally, as second form of guidance to LSCM managers an approach to manage SCA initiatives is provided. Based on the popular CRISP-DM approach to manage Analytics initiatives, a supplemented approach (sCRISP-A) was developed by incorporating insights from investigating 14 additional approaches and all data collected for this thesis. Due to the emphasis on transferability of Analytics in this thesis, the idea of creating a novel and SCA specific approach was rejected. The resulting sCRISP-A consists of eight phases with detailed tasks and actions to manage Analytics initiatives, in particular SCA initiatives. It has a stronger focus of attention in a variety of aspects identified as relevant and vital in this thesis compared to the CRISP-DM. The sCRISP-A provides guidance to manage SCA initiatives.

8.2 Limitations

This thesis is subject to limitations as usual in scientific research. A variety of limitations has been discussed in the body of this thesis already. As cumulative thesis, individual sections on the limitations are included in the articles of this research (Section 3.5.3, 4.6.1, 5.5.3 and 6.5.2). In addition, aspects are discussed regarding the scope of this research and the resulting validity for managers in section 7.1. The section reflects general limitations to this thesis.

The insights of this thesis are limited to the applied methods. All chosen methods are based on anecdotal evidence, which does not allow to quantify identified effects, the impact of presented measures or benefits Analytics can provide to organizations. Except for the explanatory case studies of article 3, the methods are exploratory in nature and aspire to provide a vast understanding of the investigated unit of analysis. The explanatory case studies are confirmatory and provide reasoning for confirmation and rejection instead of numeric parameters. Since the objective of this thesis is the *guidance* of managers, providing understanding and reasoning is understood as better fitting to the objective as compared to quantified effects. In addition, research methods to quantify effects require exploratory methods to previously identify these effects.

The form of insights of this thesis are limited by the focus of data collection. This thesis has focused on objectives, processes, practices, motivation and similar forms of phenomena. Thereby, the focus has excluded countable resource commitments such as costs or physical resources as well as advantages such as return on investment, percentage of quality improvement or time reduction in minutes. Considering the discussion above, the intended small sample size on a variety of organizations would not have created reliable measurements and these measurements would not have contributed to the research objectives. However, considering the dynamically changing analytical methods, tools and technologies, the wide range of maturity levels of organizations regarding them, and the high context dependency of their impact, no resilient measurement can be expected to be created. Further, to recapitulate the discussion on the scope of application (section 7.1), the unwillingness to disclosure that was signaled by organization is unfitting to the particularly high level of detail of such countable measurements.

With the examination of the theoretical background to the individual articles and the design of the examination setups according to the chosen research methods, the completeness of the relevant phenomenon and aspects of the unit of analysis was aimed at. However, the completeness cannot be guaranteed. Considering the individual research designs, theoretical background and examination set up could have missed causes outside the cause categories inquired for article 1, relevant coding factors for article 2, rival propositions for article 3 or barrier categories for article 4. To achieve completeness, the examination of the theoretical background of either article has been extensive and goal-oriented, and the methods were systematically and rigorously followed, as displayed by the according sections in the articles.

All research designs have been executed such that bias is minimized. However, the absence of bias cannot be guaranteed. Especially since two articles have been created solely by one researcher and accordingly the method has been applied by this one researcher alone, the individual bias of this researcher to the results has not been evaluated extensively by other researchers. To ensure the minimization of bias, the trustworthiness criteria of the chosen research methods have been investigated, the compliance to them has been tracked and the taken measure the comply have been documented in the articles.

This thesis has a total sample size of 32 interviews with 34 experts plus 46 secondary case studies. This amount is still representing a small sample size. Further, this sample size draws data from several groups including manufacturers, LSPs, retailers and Analytics providers. A larger sample size would increase confidence in the results and allow to provide a clear distinction of the results in each group. As explained in section 7.1, the sample size was limited to the response of experts and affected by perceived unwillingness to respond. Additional effort to increase the sample size was taken as long as additional observations promised compensating returns in insights, inspired or directly following the criteria of saturation.

The individual research objectives of the articles of this thesis are based on the TSP (Simon, 1973). As explained in section 1.2, this theory argues for several objectives necessary to be fulfilled such that a problem is structured. Structuring the problem of managing SCA would, in theory, allow managers to solve it in their individual organizations. However, only a choice of necessary objectives has been pursued for this thesis, since the resources to conduct this thesis have been limited. The choice was made considering the relevance of objectives and based on the strong contextual connection of the chosen objectives, which is illustrated in section 1.4.

All things considered, the results and created insights of this thesis are valid and reliable despite the limitations. The individual research objectives of the articles have been fulfilled, creating valuable insights on various aspects of managing SCA. Under additional consideration of further sources on managing Analytics initiatives, *guidance* to create value for customers with SCA and to manage SCA initiatives have been developed from the insights. Thus. a contribution to *guidance* of managers of LSCM organization in the beneficial application of Analytics to their organizations has been created, fulfilling the overall research objective of this thesis.

8.3 Future Research

This thesis calls for further research. Based on reoccurring issues of managers to motivate budget for their Analytics initiatives due to the uncertainty of the created value, research on estimating the impact is beneficial to managers. This thesis has established to evaluate the value from Analytics solutions based on the effects in the supported process and additionally the indirect effects from the supported decisions in the process. A method to operationalize this approach should be developed. Furthermore, different starting positions of Analytics initiatives and the resulting uncertainty of value need to be categorized and specific recommendations need to be developed. Regarding the TSP (Simon, 1973), this addresses a minor and detailed characteristic required to define to structure the problem of managing SCA.

Altogether, the remaining characteristics required to define to structure the problem of managing SCA according to the TSP are differences of states in the problem space, tests of these differences and the connection of operators (measures to overcome barriers in this thesis) to reduce or remove the differences. On a broader level, this would be represented by a SCA maturity model, which links measures to maturity stages. This investigation requires a different perspective on measures as compared to the perspective this thesis has assumed, since measures to advance in Analytics are specifically inquired. With a potential to identify further beneficial measures and practices to manage SCA, such an investigation represents valuable research.

More practically, further research is required in areas in which LSCM organizations display reluctance. In the evidence, the contemporary focus was identified to be on internal improvements from Analytics. Thus, research that creates motivation for the development of customer facing Analytics solutions could benefit LSCM organizations. In an affirmative and supporting effort, motivation could be created with novel methods to evaluate the impact of customer facing Analytics solutions developed by scientific research. In contrast, an investigation of the degrading competitive position of LSCM organizations in market areas absorbed by innovative digital business models based on customer facing Analytics solution could be conducted, representing a more intimidating form of motivation for investments in customer facing Analytics solutions.

Finally, while physical LSCM processes usually cross organizational boundaries, cooperation on Analytics use cases crossing organizational boundaries are rare. Mistrust and protectionism prohibit the development for holistically beneficial Analytics solutions to the Supply Chain or even the exchange of data beyond forecasts. Further, from the exchange of incorrect data due to carelessness to the exchange of fraudulent data to improve the individual position, the evidence of this thesis has captured a variety of unfavorable behavior even if data exchange agreements are in place. Thus, research is needed to estimate and show the effects of such behavior and provide scientifically sound evidence to stimulate more cooperative behavior of Supply Chain actors to enable more efficient, reliable and customer-oriented Supply Chains driven by Analytics.

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Appendix A

* phase names were not given in the original source and have been chosen by the researcher.

Approach 0: CRISP-DM

(Chapman et al., 2000)

Phase name	No. of task	Task and activities
Business Understanding	P_1.1	**Determine Business Objective** • Determination of project objectives from a business perspective and resolution of competing objectives • Determination of project success criteria
	P_1.2	**Assess Situation** • Identification of resources (human, data, computing, software), constraints, assumptions, requirements (schedule, result quality, security, legal), risks, and other factors relevant for analysis and project • Analysis of costs and benefits
	P_1.3	**Determine Data Mining Goals** • Determination of project objectives in technical terms and technical output to achieve business objectives • Determination of project success criteria in technical terms
	P_1.4	**Produce project plan** • Description of plan (steps, tools) to achieve technical objectives and resultingly business objectives and specification of review points for project plan updates • Initial assessment of analysis techniques
Data Understanding	P_2.1	**Collect initial Data** • Acquisition of data and recording of encountered problems and their resolutions
	P_2.2	**Describe data** • Surface examination of data characteristics and check against requirements
	P_2.3	**Explore Data** • Use of query, visualization and reporting techniques • Documentation of first insights, initial hypothesis, and needs for data preparation
	P_2.4	**Verify Data Quality** • Examination of data quality, documentation of quality issues and identification of possible solutions (to be decided with business knowledge)
Data Preparation	P_3.1	**Select Data** • Decision on data to be used for analysis considering objectives and technical constraints
	P_3.2	**Clean Data** • Execution of data cleaning actions, documentation of them and evaluation of their impact
	P_3.3	**Construct Data** • Creation of data with required attributes for analysis from data
	P_3.4	**Integrate Data** • Merge and aggregation of the data about objects under investigation
	P_3.5	**Format Data** • Execution of syntactic changes keeping meaning of data but necessary for the modeling

Modeling	P_4.1	**Select Modeling Techniques** • Decision on a specific modeling technique and documentation of it with made assumptions
	P_4.2	**Generate Test Design** • Planning of procedure to test quality of the model and preparation of data accordingly
	P_4.3	**Build Model** • Running of modeling tools and creation of model(s) and documentation of used parameter settings, reporting on interpretations of model and issues during modeling
	P_4.4	**Assess Model** • Interpretation and evaluation of model related to modeling domain (modeling success criteria, test design), ranking of models under account of modeling and business criteria, collection of feedback from business domain on model • Tuning of models accordingly
Evaluation	P_5.1	**Evaluate Results** • Assessment of models meeting the business objectives, testing of model in real application if possible, summary of model evaluation in business criteria
	P_5.2	**Review Process** • Quality assurance of the process by reviewing, eventually repeating activities
	P_5.3	**Determine next steps** • Decision on proceeding, initiating another iteration, or setting up a subsequent project based on project outcome, documentation of reasoning for and against options
Deployment	P_6.1	**Plan Deployment** • Determination of strategy of deployment, the necessary steps and how they are executed
	P_6.2	**Plan Monitoring and Maintenance** • Determination of maintenance strategy (incl. evaluation of correct usage) and monitoring process of deployment, documentation
	P_6.3	**Produce Final Report** • Creation of report about project (incl. summary of previous deliverables) and experiences and results, organization of concluding presentation for customer
	P_6.4	**Review Project** • Assessment of the project (positives, negatives, improvement potentials)

Approach 1: Knowledge Discovery in Databases (KDD)

(Fayyad et al., 1996)

Phase name	**No. of task**	**Task and activities**
Development of understanding**	P_1.1	**Develop Understanding** • Investigation of the application domain • Investigation of relevant prior knowledge
	P_1.2	**Identify the goal** • Identification of goal from customer viewpoint • Identification of intended use of data mining (verification of user Hypothesis or discovery of new patterns)
Create target data set*	P_2.1	**Selection of Data Set**

		• Selection of data set, sample or subset of variables to perform discovery
Data Cleaning*	P_3.1	**Data cleaning and preprocessing** • Removal of noise • Collection of information to model or account for noise • Decision on strategies to handle errors in data
Data Reduction and projections*	P_4.1	**Feature identification** • Search of useful features (to present data; depending on business goal)
Choose Method*	P_5.1	**Choose Data Mining method** • Identification of methods fitting to Business goal
Exploratory Data Analysis*	P_6.1	**Exploratory Data Analysis** • Choice of algorithms, models and parameters • Selection of hypothesis
Data Mining*	P_7.1	**Search for Patterns of Interest** • Application of chosen algorithms and models
Interpretation*	P_8.1	**Interpretation** • Interpretation of patterns • Return to any previous step, if necessary • Visualization of patterns
Acting*	P_9.1	**Use gained Knowledge** • Integration of knowledge into systems, documentation of it and reporting on it • Evaluation and resolution of potential conflicts with previously believed (or extracted) knowledge

Approach 2: Steps involved in using advanced analytics

(Bose, 2009)

Phase name	No. of task	Task and activities
Developing Understanding*	P_1.1	**Develop Understanding** • Investigation of application domain • Investigation of the goals of advanced Analytics process
Acquiring data*	P_2.1	**Get access to data** • Acquisition or selection of a target data set
Data Integration*	P_3.1	**Integrate data set** • integration and Evaluation (not further specified) of data set
Data Preparation*	P_4.1	**Prepare data** • Data cleaning, preprocessing of data (standardizing) and transformation of data
Modeling*	P_5.1	**Modeling** • Data exploration and visualization • Development of model and building of hypothesis
Algorithm selection*	P_6.1	**Algorithm selection** • Choice of suitable algorithm for data or text mining • Extraction of patterns
Interpretation*	P_7.1	**Interpretation** • Interpretation • Visualization
testing*	P_8.1	**Testing** • Testing of results and verification

Using and maintaining*	P_9.1	**Use** • Use of discovered knowledge • Maintaining knowledge

Approach 3: PADIE Technique

(LaValle et al., 2010)

Phase name	No. of task	Task and activities
Document existing processes and applications	P_1.1	**Identify Value** • Identification of value delivered to the customers (product/Service, customers)
	P_1.2	**Identify applications** • Identification of applications used to drive the business (IT Systems and Management tools)
	P_1.3	**Identify processes** • Identification of core business processes (operational and transactional processes, touch points with external parties)
Identify data and insights	P_2.1	**Identify data** • Identification of data in the processes
	P_2.2	**Identify insights that can solve pain points and create value** • Identification of questions that address pain points, create revenue, reduce cost or increase margins • Identification of data sources • Execution of analytical inquiries
Embed analytic insights	P_3.1	**Embed insights** • Determination of best approach for embedding insights into operations (enhance existing applications, new analytical solutions, changing business rules, changing workflow, simulations for understanding scenarios) • Embedding of insights

Approach 4: Meaningful data integration

(Bizer et al., 2012)

Phase name	No. of task	Task and activities
Define	P_1.1	**Define the problem** • Definition of business problem or the query to be answered
Search	P_2.1	**Search candidate data** • Identification of data (elements) that fit the problem
Transform	P_3.1	**Extract, Transform and Load data** • Obtaining the data in appropriate formats and stored for processing
Entity Resolution	P_4.1	**Verify data** • Verification whether data is unique, relevant and comprehensive, exclusion of data without relevance
Answer the query/solve the problem	P_5.1	**Compute answer** • Use of domain-specific computations

Approach 5: Outline of big data analytics in healthcare methodology

(Raghupathi and Raghupathi, 2014)

Phase name	No. of task	Task and activities
Concept statement	P_1.1	**Establish need** • Establishing the need for (big) data analytics project • Formulation of a concept statement and description of project's significance • Business expert/customer description of complexity and trade-offs from his/her point of view
Proposal	P_2.1	**Develop proposal** • Identification of addressed problem, its importance and the interest to the users, why the Analytics approach has been chosen (opposed to other approaches) • Identification of background material (on domain, prior projects and research on the domain)
Methodology	P_3.1	**Proposition** • Breakdown of concept statement into propositions
	P_3.2	**Variable Selection** • Identification of relevant dependent and independent variables • Identification of data sources
	P_3.3	**Data preparation** • Collection of data, description of data and transformation of data
	P_3.4	**Platform/tool selection** • Evaluation of different platforms/tools and their selection
	P_3.5	**Apply Analytics techniques** • Creation of conceptual model • Application of techniques (in series of iterations, What-if analyses) • Identification of results and insights
Deployment	P_4.1	**Evaluation and validation** • Testing and validation of models and their findings • Presentation of models and findings to stakeholders (for action) • Implementation in staged approach with feedback loops to reduce risk

Approach 6: Job Task Analysis Process

(INFORMS, 2014)

Phase name	No. of task	Task and activities
Business Problem Framing	P_1.1	**Receive & refine the business problem** • Identification of problem statement (business opportunity or threat/issue) and the various perspectives on it from different representatives (collect and systemize them to frame the problem) • Obtaining of definitions of organizational business language and key terms
	P_1.2	**Identify Stakeholder** • Identification of interested and affected stakeholder and their constraints • Planning of encouragement of participation and stakeholder communication and management strategies

	P_1.3	**Determine whether problem is amenable to an Analytics solution** • Identification of organizations control over investigated process, access to data, solvability of problem, and ability to deploy solution by the organization
	P_1.4	**Refine Problem Statement & delineate constraints** • Creation of problem statement more accurate, more appropriate to stakeholders, more amenable to available Analytics tools/methods • Definition of constraints to the projects (analytical, financial, political)
	P_1.5	**Define an initial set of business benefits** • Definition of initial set of business benefits (quantitative or qualitative)
	P_1.6	**Obtain stakeholder agreement on the problem statement** • Obtaining of permission to proceed with the project (previous steps may have to be repeated until stakeholders agree)
Analytics Problem Framing	P_2.1	**Reformulate business problem statement as an Analytics problem** • Translation of business problem into analytical approach (analytical results, needed resources, taken analysis and actions, effect on organization), e.g., by QFD • Systemization of customer requirements
	P_2.2	**Develop a proposed set of drivers & relationships to outputs** • Definition of input/output functions of the problem (in form of ideation) and communication of them to the team to set directions for actions • Communication of the preliminary assumptions
	P_2.3	**State the set of assumptions related to the problem** • Set of boundaries to the problem based on assumed input drivers
	P_2.4	**Define key metrics of success** • Negotiation, publishing and commitment to tangible metrics and tracking planned
	P_2.5	**Obtain stakeholder agreement** • Communication/Coordination of assumptions to stakeholder (including the analytics project team) and obtaining acknowledgment from them to proceed
Data	P_3.1	**Identify & prioritize data needs and resources** • Identification of needed hard data and determination of relevant confidence levels
	P_3.2	**Identify means of data collection & acquisition** • Identification of the best way of data collection (or what can be achieved with collectable data to determine whether the effort of data collection is justified)
	P_3.3	**Determine how and why to harmonize, rescale, clean & share data** • Identification of data quality and determination of cleaning strategies
	P_3.4	**Identify ways of discovering relationships in the data** • Application of techniques to understand data
	P_3.5	**Determine the documentation & reporting of findings** • Determination of communication strategy of findings to (different) stakeholders
	P_3.6	**Use data analysis results to refine business & Analytics problem statement** • Reframing of the problem statements based on hard data
Methodology (Approach) Selection	P_4.1	**Identify available problem-solving approaches (methods)** • Choice between descriptive, predictive, and prescriptive approach
	P_4.2	**Select software tools**

		• Evaluation of available time, accuracy of needed model, relevance of methodologies, accuracy of data, data availability, staff & resource availability, methodology popularity (choose most relevant, not most popular!) • Communication of chosen approach to stakeholders and the pros and cons • choose software system
	P_4.3	**Test approaches (methods)** • Building of training and test sets from data to prepare testing of the model
	P_4.4	**Select approaches (methods)** • Choice of most accurate model adhering to time and cost constraints
Model building	P_5.1	**Identify and build effective model structures to help solve the business problem** • Consultation of subject matter expert on expected model characteristic • Adaption of data to methodology, transform data, building of model and refining of model, as well as assessment of competing models' performance honestly (e.g., performance in intended use/in real-time production environment)
	P_5.2	**Run and evaluate the models** • Assessment of appropriateness of model to intended use (e.g., interoperability), and based on testing data
	P_5.3	**Calibration of models and data** • Refining of model and data to eliminate weaknesses
	P_5.4	**Integrate the models** • Pre-planning of integration of model into production environment (which inputs are needed, and which outputs are given)
Solution Deployment	P_6.1	**Perform business validation of model** • Evaluation of adherence of result to original problem, and changes in business context (don't adjust to "play politics") • Peer review for technical correctness • Communication of answers and key assumption (don't communicate models too detailed)
	P_6.2	**(alternative 1) Deliver report with finding** • Creation of report with clear message (clear course of action/no actions plus reasons)
	P_6.3	**(alternative 2) Create model, usability, and system requirements for production, deliver production model/system** • Creation of production system with clear message (clear course of action/no actions plus reasons)
	P_6.4	**Support deployment** • Planning of deployment strategy and planning of monitoring and maintenance after deployment (incl. contact with key stakeholders) • Creation of documentation and training documentation
Model Lifecycle	P_7.1	**Document initial structure** • Documentation of key assumptions made about business context and Analytics problem; data sources and data schema; methods used to clean and harmonize data; model approach and mode review; written code; recommendations for future improvements • Backup of the documentation (in redundant storage places)
	P_7.2	**Track model quality** • Evaluation of adherence to evaluation criteria and quality parameters over time

	P_7.3	**Recalibrate and maintain model** • In case of quality decay, adaption of model to new data and changed business problem
	P_7.4	**Support training activities** • Enabling users to understand and use the results
	P_7.5	**Evaluate the business benefit of the model over time** • Tracking of business benefit in business indicators and terms (e.g., saved money, increased profit, increased return on assets) by simulating what organization would have done without the model

Approach 7: Framework for implementation of Big Data projects in firms

(Dutta and Bose, 2015)

Phase name	No. of task	Task and activities
Business Problem	P_1.1	**Business Problem** • Development of sound understanding of business process or problem, incorporation of directions from senior management and stakeholders (involved business units) • Set of expectations of stakeholders
Research	P_2.1	**Research** • Understanding of how similar problems have been addressed • Development of overview of IT and analytical infrastructure within organization • Development of understanding of technologies and vendors on the market
Cross functional team formation	P_3.1	**Cross functional team formation** • Institutionalization of a cross functional team, incl. Stakeholder business units, IT experts, data modelers, scientists, experts in cognitive science or customer behavior and business decision makers
Project Roadmap	P_4.1	**Project roadmap** • Development of project roadmap, incl. Activities, timelines and designated person
Data collection and examination	P_5.1	**Data Collection and examination** • Examination and analysis of existent organizational data (structured and unstructured) • Filtering of relevant data and structuring of it (create meta data, tagging)
Data Analysis and Modeling	P_6.1	**Data Analysis and modeling** • Analysis of data and discovering of insights
Data Visualization	P_7.1	**Data visualization** • Development of visual representations of data helping insight generation/pattern detection
Insights generation	P_8.1	**Insights generation** • Transformation of discoveries in data into actionable insights for organization
Integration with IT System	P_9.1	**Integration with IT System** • Deployment and integration of models and visualization tools into IT system • Testing of models and tools and resolution of issues
Training people	P_10.1	**Training People** • Training of people on new tools and building of acceptance, disincentivizing the use of previous tools

Approach 8: OR Phases

(Hillier and Lieberman, 2015)

Phase name	No. of task	Task and activities
Defining the Problem and gathering data	P_1.1	**Defining the Problem** • Development of a well-defined problem statement (appropriate objectives, constraints, interrelationships, possible alternative courses of action, time limits for decision-making, …) • Consultation of stakeholders/reflect stakeholder position and building of understanding of how solution is used by decision makers/effects stakeholders • Development of long-run profit indications (or other relevant indicators such as stable profit, increased market share, improve worker morale, provide product diversification, maintain stable prices, increase company prestige)
	P_1.2	**Gather data** • Collection of necessary data, installation of new systems for data collection if necessary • Extraction of relevant data from organizational databases
Formulating a Mathematical Model	P_2.1	**Reformulating Business Problem** • Reformulation of business problem into form that is convenient for analysis (into mathematical problem that represents the essence problem). → The model is an abstraction of the subject of inquiry and idealized versions • Execute evolutionary process to build more elaborate models
	P_2.2	**Determining the values of the model parameters** • Gathering of relevant data • Development of overall measure of performance (tangible such as profit or abstract such as utility)
	P_2.3	**Testing Models and choosing the best representation of the problem** • Testing of model predictions correlating to real world
Deriving solutions from the model	P_3.1	*[this phase and the next iterate]* **Develop procedure to derive solution** • Application of algorithm on digital presentation of the model
	P_3.2	**Post-optimality Analysis** • Testing of practical success of the model, since the solutions are optimal only with respect to the used model • Testing whether solution is "satisficing", which is "good enough" for the managers for the problem at hand • Addressing of what-if questions (what would happen, if assumptions would be different) • Sensitivity analysis to determine, which parameters are most critical • Development of alternative solutions based on Analyses to be presented to management
Testing the Model	P_4.1	*[this phase and the previous iterate]* **Model Validation** • Review of model (internal team members and externals) • Review of plausible behaves of model • Retrospective test (use of historical data to reconstruct past and determine how well the solution would have performed) • Documentation of validation process (for increasing confidence in model and identify issues in the future)

Preparing to apply the model	P_5.1	**Install (well-documented) system** • Integration with other systems (e.g., databases, Management information systems) via interface programs • Testing of program • Development of maintenance procedure
Implementation	P_6.1	**Implement system** • Assurance of accurate transformation from model to system • Communication to management of accomplishing the objectives
	P_6.2	**Use** • Assurance of decisions being made according to the solution • Collection of feedback during solutions lifetime • Maintenance if model if model assumptions change
	P_6.3	**Documentation** • Documentation of methodology for reproducibility

Approach 9: MODA's 10 step model

(Copeland, 2015)

Phase name	No. of task	Task and activities
Understand how day-to-day operations work	P_1.1	**Analysts shadow operating staff** • Gaining of understanding on operations and their characteristics (resources, schedule), prioritization/decision-making, data collection
Identify areas where data could help	P_2.1	**Examine data on operations** • Examination of data and ideation of improvement potential from data and evaluation of assumptions with operations teams • Identification of potentially needed steps to provide improvement by examining the problem, required data, the goal of the data usage, need resources and commitment for the project
Form a project plan	P_3.1	**Design project plan** • Development of project plan together with operations teams • Coordination on work packages, needed data and their eventual collection, and timeline and milestones
Understand data context	P_4.1	**Understanding data** • Analysts study data, their collection (and stored) and meaning/interpretation in the original context • Examination of data characteristics and identification of potential issues with data
Create a Memorandum of Understanding (MOU)	P_5.1	**Formal agreement** • Establishment of a formal agreement (memorandum of understanding) between Analysts and operations team • Inclusion of agreement of purpose of data sharing, privacy and data protection, ensures transparency and commitment for each party involved
Integrate data	P_6.1	**Integration of data** • Identification of systems used for data collection and storage and appropriate method for connecting data • Creation of technical connections of data and mapping of data together

Test hypotheses	P_7.1	**Hypotheses** • Creation of hypotheses in collaboration with operations teams • Choice of analytical techniques • Testing of hypotheses/analysis of data • Communication of results to operations team
Service delivery team review	P_8.1	**Operations team review** • Review of data model by operations teams, checking of analysis and correctness of interpretations (pilot could be presented) • Inquiry for deviations from expectations and their reason as well as suggestions for alterations of the model • Updating of models if needed • Design of field tests/pilot studies, development of performance criteria for the field test, and examination of technical requirements
Automate the process	P_9.1	**Integration into systems of operations teams** • Identification of necessary system changes for automating the model and analysis of integration into systems of operations teams and their workflow • Creation of maintenance/performance review schedule
Implement solution	P_10.1	**Roll-out** • Roll out of solution and integration in operations • Creation of training • Creation of criteria for measuring performance over time
Delegate responsibility for the data model	P_11.1	**(Optional) Responsibility is delegated to operations team** • Transfer of responsibility of the solution to operations team, its management and advancement

Approach 10: Statistics live cycle

(Kenett, 2015)

Phase name	No. of task	Task and activities
Problem Elicitation	P_1.1	**Analysts inquiry** • Inquiry of details on the problem by analysts for better understanding of problem, facts and assumptions • Collection of data on the problem and context (e.g., process maps, site visits) by analysts
Goal Formulation	P_2.1	**Clarify the problem** • Elaboration of discussion on the problem to formulate a goal for analysis
Data collection	P_3.1	**Observation of data collection** • Participation in or observation of data collection by analysts to gain understanding of the data and its context as well as identification of possible sources of variation • categorization of sources of variation in controllable or not controllable • Evaluation of integrity of signal and collected data
Data Analysis	P_4.1	**Perform Analysis** • Identification of appropriate Analysis technique • Conduct of analysis
Formulation of Findings	P_5.1	**Translate findings of Analysis into relevant information** • Formulation of findings such as benefits, and core values become clear

		• Customer oriented reporting of findings by identifying consequences from findings to the customers and understanding the context of the customers problem
Operationalization of Findings	P_6.1	**Put insight into operation** • Transformation of results in accessible and receptable/repeatable form • Design of translation from analysis to recommendations on actions
Communication	P_7.1	**Communicate findings to customer** • Communication of findings in language of the customer and focused on problem • Creation of visualizations to support communication • Creation of different publications for different audiences
Impact Assessment	P_8.1	**Assessing the impact of the Analysis** • Assessment of impact including economic values, probabilities of solution to have the accounted impact, and what portion of the problem is solved (e.g., practical statistical efficiency)

Approach 11: Data Analytics Lifecycle

(Dietrich et al., 2015)

Phase name	No. of task	Task and activities
Discovery	P_1.1	**Learning the business domain** • Determination of amount of domain knowledge, which data scientists need to develop solution for the initiative
	P_1.2	**Resource scoping** • Assessment of available resources (technology, tools, systems, data, people) for the initiative and for operationalization • Assessment of level of analytics sophistication of customer (tools, technologies, skills) for executing the domain and long-term usage of solutions • Inventorization of available data and assessment of fit to initiative objective and resulting gaps; determination of data to obtain elsewhere • Division of initiative in multistep objectives ("journey") and determination of achievables for current project and effort for subsequent steps • Assessment of needed skills and expertise (analytical and domain) against available expertise
	P_1.3	**Framing the problem** • Formulation of problem statement (incl. current situation and challenges) and checking with key stakeholders • Identification of business objective, success criteria and failure criteria, documentation of them and sharing with project team and sponsors (to check against expectations)
	P_1.4	**Identify key stakeholders** • Identification of stakeholders (impacted by or benefitting from project) and their stake/interest • Estimation of stakeholders’ expected activities along the initiative
	P_1.5	**Interview the analytics sponsors** • Consultation of project sponsor for expectations and their understanding of the business problem/identification of

		stakeholder biased expected solutions (see source for example interview questions)
	P_1.6	**Developing initial Hypotheses** • Development of ideas to test with the data and collection of ideas from stakeholders • Data exploration for idea development
	P_1.7	**Identifying potential data sources** • Identification of needed data for the initiative and their specification • Execution of data exploration: identification of data sources, capturing of aggregated data sources, review of raw data, evaluation of data structure, tools and scope data infrastructure needed
Data Preparation	P_2.1	**Preparing the Analytic Sandbox** • Presentation of justifiable benefits and convincing of data owners to collaborate by sharing data • Collection of data from sandbox environment
	P_2.2	**Perform ETLT** • Determination of data quality and set-up of transformations to be executed • Loading and transformation of data for pattern search in the sandbox environment • Inventorization of data in the sandbox environment
	P_2.3	**Learning about the data** • Building of understanding on available data and updating information on data source inventories and gaps of needed data (available + not accessible; available + accessible; to be collected; to be acquired from 3rd party)
	P_2.4	**Data conditioning** • Cleaning, normalization and transformation of data (and categorization of data by usefulness)
	P_2.5	**Survey and Visualize** • Visualization of data to gain overview and recognize high-level patterns
Model Planning	P_3.1	**Data exploration and variable selection** • Data exploration (with focus on understanding relationships) for variable selection
	P_3.2	**Model Selection** • Choice of analytical technique (or list of candidate techniques) fitting to initiative objective • Choice of statistical software package and infrastructure for modeling
Model Building	P_4.1	**Model Building** • Development of datasets for training, testing and production • Development and execution of analytical models and iterative evaluation using training and test data scores • Recording of assumptions, decision and adjustments made during the process

Communicate Results	P_5.1	**Communicate the Results** • Comparison of results to established success and failure criteria • Identification of best way to communicate results to team members and stakeholders (incl. Caveats, assumptions and limitations) • Identification of relevant talking points (surprises, validated ideas/hypotheses, most significant findings) • Reflection of findings in business terms and value • Description of subsequent steps and responsibilities of team members, stakeholders and other business units/teams (e.g., IT setting model into production) • Derivation of recommendations for future projects based on learnings and encountered obstacles • Presentation of results to stakeholders
Operationalize	P_6.1	**Operationalize** • Set-up of pilot project to deploy work in controlled way and learning from the performance of the pilot in a production environment • Application of adjustments before full deployment • Creation of on-going monitoring with bounds of operation of the model and alerts triggered in out-of-bounds situations

Approach 12: Fast Analytics/Data Science Lifecycle

(Larson and Chang, 2016)

Phase name	No. of task	Task and activities
Scope	P_1.1	**Define scope** • Definition of problem statement and objective • Record of operating boundaries and expectations
Data Acquisition/Discovery	P_2.1	**Data acquisition/discovery** • Access, assessment and visualization of data to discover value and use of data sources
Analyze/Visualize	P_3.1	**Analyze/Visualize** • Visualization of data and exploratory data analysis (identification of relationships and parameters for analytical models) • Creation of side products (dashboards, scoreboards), which need to be validated
Model/Design/Development	P_4.1	**Model/Design/Development** • Application of analytical models and techniques to data
Validate	P_5.1	**Validate** • Iterative validation of the analytical models to produce model with minimal error • Identification of need for more data sources
Deployment	P_6.1	**Deployment** • Adding models to the production environment to provide their functionality
Support/feedback	P_7.1	**Support/feedback** • Collection of feedback about the analytical models performance in production and use, and adjustment of model to changes (including changes in organization and industry)

Approach 13: The eight-step data analytics lifecycle model

(Song and Zhu, 2016)

Phase name	No. of task	Task and activities
Business Understanding	P_1.1	**Business Understanding** • Identification and specification of business problem with business benefits from solving it
Data Understanding	P_2.1	**Data Understanding** • Identification of relevant data sources and sets as well as requirements
Data preparation	P_3.1	**Data Preparation** • Data preparation and integration, execution of ETL, virtualization
Model Planning	P_4.1	**Model planning** • Selection of algorithm/technique fitting to data, setting of parameters, establishment of evaluation criteria, determination of when and how to change algorithm and techniques
Model building	P_5.1	**Model building** • Development of problem specific algorithms for a given problem and data set for new problems (if existing techniques or tools are not effective)
Evaluation	P_6.1	**Evaluation** • Evaluation of models and results to determine success or failure against business question
Deployment	P_7.1	**Deployment** • Implementation of model in a production environment
Review & Monitoring	P_8.1	**Review & Monitoring** • Constant review of performance of the solution and adjustments for improvement (add new data, extending the scope, adopting new techniques and tools, adopting new visualization)

Approach 14: SEMMA

(SAS, 2017)

Phase name	No. of task	Task and activities
Sampling	P_1.1	**Sample** • Sampling of data with significant amount of information to the problem
Exploring	P_2.1	**Explore** • Search for anticipated relationships, unanticipated trends and anomalies to gain understanding of data
Modifying	P_3.1	**Modify** • Creation, selection, and transformation of variables • Selection of analytical model
Modeling	P_4.1	**Model** • Use of analytical tools to achieve desired outcome
Assessing	P_5.1	**Assess** • Evaluation of usefulness and reliability of findings

Appendix B

Measures to overcome barriers in SCA

No.	Measure	Explanation
1	(Permanent) cross-functional teams to take all relevant perspective into account during solution development	Cross-functional team (business, Analytics, IT, data) are build either for specific Analytics initiatives or as permanent teams with their own backlog of initiatives. These teams provide various perspectives on relevant issues in different stages of the Analytics solution development and deployment (e.g., data accessibility, user requirements, deployment environment) such that the solutions quality and functionality is ensured and coordination effort for it is reduced.
2	Strategic roadmap of developing Analytics capabilities to support organizational goals to build the capabilities and foundation for Analytics	A strategic plan on developing Analytics capabilities and building a foundation for it improves available tools, technology and (human) resources and, thus, the execution of Analytics initiatives and the performance of the developed solutions. However, for non-technology organizations building these capabilities should be connected to the organizational strategy and not for the sake of Analytics itself. This way, employees recognize the relevance of the roadmap and show openness to it.
3	Actively recruiting leadership and employees which are savvy with and open to Analytics to gain acceptance and broaden use of it	Recruiting leadership, which is familiar with Analytics and open to it creates the commitment, and results in a push from leadership to use Analytics. Recruiting employees for other position, which require the use and daily work with Analytics, results in higher acceptance and reception for Analytics solutions as well as collaboration with Analysts.
4	Analytics initiatives involve users early and regularly in agile solution development to develop more need fitting solutions and create acceptance	The solution development process of Analytics often requires adaptation to encountered discoveries and issues, which are highly dependent on the business context. Further, the solution must fit the business users' needs to be beneficial. Thus, agile project management methods (especially including user stories) are used and users are involved early and often to make progress in iterations where feedback on the development progress and prototypes is collected (e.g., the residual between prototype and expectation), and to produce solutions that fit the business users' needs. This works if the environment allows to execute the agile sprints as agreed and doesn't create chaos. Involving users regularly further creates touching point of the users with the solution and increase their acceptance.
5	Analysts review the fit of the expressed analytical need of the users to their business need to create a better fitting Analytics solution	While business users are usually not skilled to translate their business needs to an analytical need, users develop first ideas of the Analytics solution they want. Analysts must critically review the fit of the expressed analytical need to the business need and recommend justified changes in exchange with the users before the initiative starts. This requires openness on the user's side as well. The step might occur involuntarily, if Analysts determine the business need fitting solution by discussion later in the initiative, not assuming the responsibility of reflecting the assignment critically.
6	Formal agreement between business users and Analysts on Analytics initiative to establish commitment for solution and willingness to use it	A formal agreement is concluded such that the users are committing to the expressed need, and further to collaboration, scope of the initiative, and fulfilling the users' tasks (e.g., contributing to providing the data including taking part in pushing data owners to provide data). Thus, eventual Analytics solutions in which users actually have low interest in are sorted out early.

7	Analytics resources set up as hybrid approach between centralized and decentralized unit to achieve closeness to business and oversight	Instead of setting up either a center of excellence or placing decentralized Analysts in business units, a hybrid approach of both is taken. In the central unit, Analysts can collaborate easily and develop solutions together for more complex and broader issues, the Analysts can be deployed more flexible, software and tools are controlled centrally, and the central unit has certain political power in the organization. Decentralized Analysts are closer to the business user, gain trust and collaboration easier, and also address smaller analytical needs, while understanding the business side better. Decentralized Analysts can source special capabilities from the central unit, and Analytics solution developed by the decentralized Analysts in close collaboration can be distributed to other units via the central unit.
8	Pro-active Analytics training for leadership and employees to demystify, answer questions, create acceptance, knowledge and use cases	Training on Analytics is provided for leadership and employees outside of a specific initiative or intended application. Besides the creation of knowledge, the trainings are supposed to demystify Analytics and set realistic expectations, provide a forum for questions, build capabilities to create use cases in the business units and often create use cases in the trainings already, set a foundation for collaboration (e.g., introduce point of contact) and strategically create key users in business units, who can act as knowledge distributers.
9	Convert data collection from manual to automatic and constantly increase datafication of processes to increase data quality and availability	To address data quality, the source of data is considered as most relevant. Automation of data collection is used to avoid errors of manual data collection, while malfunctions of sensors still must be controlled for. Further, more sources are created and more sources, that collect data not intended for Analytics are transformed. Thus, more data in analyzable quality is available. Electronic business models have a natural advantage on this.
10	Data ownership and responsibility for documentations is assigned to business units to increase data quality and transparency	The responsibility and ownership of data sources is assigned to business units, such that these are becoming more transparent. As firsthand user of the data, the business units are therefore more aware of needed improvements and might eventually have the control over data quality, since they collect some data by themselves.
11	Central unit evaluates data sharing with Supply Chain Partners to create oversight	A central unit evaluates, whether data sharing with Supply Chain Partners is beneficial and justifiable. It further can evaluate conflicts of interest. As a central unit, it could overcome unwillingness to share data of individuals, while it would be beneficial for the organization, if the unit is knowledgeable of the sharing request.
12	Designated programs and (central) units for data quality to improve data quality	Programs and (central) units are created and established, which are concerned with improving data quality, structure of data sources and identify deficiencies. A dedicated unit is a more stable point of reference, since it can initiate programs to improve data quality and is a point of contact for identified data quality issues.
13	Employees are challenged to provide data driven justification for their decision-making to increase use and raise acceptance for Analytics	The somewhat more demanding approach to achieve a broader data driven acting organization is to ask and challenge employees to provide data that justify their decisions before actions are taken. This demand must come from a leadership level, which subsequently must act as the data recommends or justify otherwise. Two assumptions build this approach. One, employees are getting used to it and eventually experiencing the benefits and value. Two, the demand for using Analytics is comprehensible and plausible for the employees since it directly goes into decision – it is not for the sake of Analytics. This creates acceptance.

14	Systematically evaluate data sources for use cases to identify use cases	Data Sources are systematically addressed and evaluated for viable use cases that could be derived from the data. Including users that would work with the developed Analytics solution in the evaluation is vital to avoid development of not needed and unused solutions.
15	Co-location of analyst and business users during Solution development for improved collaboration to raise acceptance	A form of collaboration in which Analyst and Business users are co-located. The Analysts gain the opportunity of getting answers on questions on short notice. In turn, the business users gain insight into the solution development and can ask questions. This increases acceptance, eases solution development and improves the fit of solution to business needs.
16	All affected business functions create consistent story on relevance to build a foundation for Analytics to leadership to motivate investments	As a "one story to the customer" approach, all business functions that will eventually be involved in Analytics initiatives and, thus, depend on a good organizational, technological and data foundation, coordinate a clear message about the necessity of that foundation and communicate it individually to the leadership. The momentum behind the coordination, as expressed by the harmonized message, is supposed to motivate and convince investments.
17	Supply Chain Partners are requested by contracts/contract clauses about data sharing to create collaborative Analytics initiatives	While any sharing of data should be documented in a legal contract or a contract clause, Supply Chain Partners are increasingly requested to share data for reasons of efficiency and transparency regarding their role in the Supply Chain (e.g., for control service level agreements). This data can be a starting point for collaborative Analytics initiatives, which build on the existing data exchange. Including data sharing regarding to the Partners' roles in the contract negotiations increases the potential for collaborative initiatives but requires educating the negotiators.
18	Data collection for Analytics solution (or else) is set up such that personal data is not collected to avoid issues related to privacy	If possible, the data collection on processes or activities, for which a potential collection of personal data could take place and privacy issues might be raised, is designed such that the personal data is explicitly not collected. This reduces the need for restrictions on the data, which might omit other analysis, unrelated to the personal information.
19	Validation rules and automated interpretation of manual data collection to increase data quality	Certain manual data collection cannot be avoided. For single fields, validation rules that limit the possibilities of entries to reasonable values can be introduced. If free text is relevant for the process due to complex information needed to be collected, automated interpretation (e.g., machine learning models) can be introduced to translate the data into fast usable information (e.g., categorization of issues). Further, common and apparent errors in data can be automatically resolved during the ETL process of the data to the Analytics solution. Thus, issues with data are resolved by rules and automation, likely identified and developed with Analytics.
20	Supply Chain Partner are motivated by clear win-win Analytics use cases to motivate collaborative Analytics initiatives	Collaborative Analytics initiative with Supply Chain Partners are motivated based on use cases which clearly highlight the benefit of the Partner. This benefit might be indirect from the Analytics solution (e.g., more sales due to improved product availability, higher efficiency due to improved forecast). A small and slow start may be needed to create examples, on which larger initiatives can build on.
21	Creation of Organization profile that appeals to analytical talent and actively targeting talent to gain access to talent	To motivate analytical talent to become interested in working for the organizations, organizations must first raise awareness in that peer group, that the organization has a need for that type of human resource. Thus, conventions, exchange platforms and universities must be addressed. Second, the organization must display the challenging analytical problems and questions that are worked on.

22	Centralize data in a data lake and create an open data policy to increase access to data	Centralizing existing data in a data lake concept. This concept becomes necessary for data from systems which are becoming obsolete and is optional for all other collected data. Preferably, the data should be stored in a structured form such that it can be analyzed. Further, this data should be open according to the open data concept on the condition the data owner has no reasonable objection against providing it for further use, the use is legal, or the use does not violate privacy and confidentiality rules. While the two concepts do not depend on each other, they create accessibility to existing data.
23	Analysts (temporary) assume business responsibility of focal decision process to overcome missing openness and acceptance	A form of collaboration in which Analyst assume the responsibility for certain decisions of business users after a period of observing and collaboratively executing the decisions. Due to participating in the decision-making, Analysts develop deeper understanding of the decision-making process and can develop and improve an Analytics Solution. This measure shall overcome missing openness, acceptance and collaboration from the business user in the solution development process. After deployment, the business user resumes responsibility in form of monitoring the solution.
24	Employees are enabled to do self-service Analytics and are regularly feedbacked by Analysts to broaden Analytics abilities and resources	Self-service Analytics are means for employees to pull relevant reports, KPIs and data for individual analysis in a limited scope. The tools used are usually developed in Analytics initiatives and catered to the individual roles of the employees, which resultingly have increased ability to do data driven decision-making while reducing their requests for data due to the solutions. Since this ability can also result in erroneous application of analytical techniques, Analysts must regularly feedback users to mentor them on their Analysis.
25	Automatic re-training loop for low performing Analytics solutions to overcome data shortage	Due to data shortage, some modeling and training methods, which would require more data to increase accuracy, are usually not deployable. In deploying them with a limited functionality and constant re-training on new data and decisions, they can be improved over time while the necessary data for high accuracy is collected.
26	Business units are allocated with designated Budget for Analytics (and process improvement) to motivate identification and execution of use cases	Due to allocated but designated budget, business units are motivated to identify use cases for Analytics and execute them with Analyst. In turn, to avoid misguided investments, the Analysts should check the generated value and process relevance of the use case.
27	Analytics resources are located in existing process improvement units to exploit structures and create openness	In organizations with existing process improvement units, Analytics resources are introduced as a new tool of the unit to exploit the existing organizational structures as well as existing acceptance and openness for these units.
28	Process data are technically separated from personal data for Analytics purpose to avoid issues related to privacy	For data collected on processes or activities, in which personal data are collected and privacy issues might be raised, technical restrictions are introduced. Data are technically stored such that they are separated before any access can take place or not accessible together. Since the employees are usually aware of data about their activities being collected, these technical restrictions should be actively communicated. Thus, less need for restrictions on the data of the whole process are required, which might omit other analysis, unrelated to the personal information.

29	Documentation on analytically used data, their preparation, and developed Analytics Solutions to create oversight and build foundation	To reduce long-term effort, analytically used data, relevant ETL-Processes, actions of preparation, integration and data transformation, and developed Analytics solutions are documented. Further, they are connected to the data sources and made visible, such that the knowledge on the existence of the documentations is spread and useful. Due to the reusability, this contributes to building a foundation for Analytics. The documentation is further supposed to reduce redundant efforts and create oversight about existing Analytics activities.
30	Analytics solutions are delivered with trainings (documentation, seminars, videos) to ensure usage of solutions	Various forms of trainings are used to ensure that users understand the solutions. This includes initial trainings but also measures to ensure long-term usability, which includes static documentations or dynamic forms such as videos or webcasts.
31	Employees are enabled to become citizen data scientists to broaden Analytics resources	Employees already working on Analytical tasks but who are not recognized for it with their role are uplifted to official Analyst roles. With their knowledge and additional Training on Analytics and the business process or unit they occupy, they become an Analytics resource in their respective process/unit and can execute analytical tasks and trainings.
32	Restrictions on accessing and analyzing data are transparently established and enforced to secure data and gain acceptance	Restrictions on accessing and analyzing data are established in a code of conduct (e.g., part of data governance), which is made transparent and provided trainings on for all employees. The responsibility is given to designated teams for data security and legal issues. The data security team and the legal team are providing assistance in edge cases, for which Analysts are required to get an evaluation. The restrictions are enforced by organizational and technical measures, such as formally reminders in potentially critical situations and by access restrictions. This restriction ensures privacy and confidentiality. Transparency on restrictions and their enforcement creates trust in privacy and confidentiality of data from employees and Supply Chain Partners and, thus, their acceptance.
33	Enhancing exchange and collaboration of Analysts to address complex problems and improve oversight	The solution-oriented exchange and collaboration of Analysts can be addressed by tools of collaborative solution development and co-location. Formal and informal exchange unrelated to solution development can be addressed by topic specific events, workshops, communities of interest, collaborative learning activities or get-togethers. Both increase the visibility of skills and, thus, contribute to focused requests for collaboration on complex issues. Further, this exchange increases visibility on organization-wide analytical activities and creates oversight. Collaborative learning supports Analysts to stay on the edge of innovative methods but may go beyond agreed responsibilities and requires self-motivated Analysts.
34	Estimation of benefits from Analytics solution based on comparable solutions or engaged inefficiency to argue for tangible value	To argue for the value of a solution, a standard way is to choose use cases based on comparable solutions deployed in comparable processes of other business units or organizations, or based on targeted inefficiencies. The value of a solution development is estimated based on the comparable solution or the elimination of the inefficiency. Thus, the value from Analytics can be expressed in more tangible terms for users and sponsors, even if the effect from Analytics is indirect.

35	Estimation of benefits from Analytics solution based on a hypothetical Prototype to argue for tangible value	To argue for the value of a solution, an unconventional way in situations with very costly data collection and no available data for a prototype is to create a simulation of the business process that creates the data such that a hypothetical prototype from that data can be created. However, this hypothetical prototype is just a strategy to test ideas, as it might be necessary for reinforcement learning, and creates an estimate of the potential value by making the value more tangible to motivate investments. The prototype is nowhere near a deployable solution.
36	Estimation of benefits from Analytics solution based on a prototype/proof-of-concept to argue for tangible value	To argue for the value of an Analytics solution, a conventional way for situations, in which the effect of the solution is hard to estimate or the feasibility unknown, is to create a prototype/proof-of-concept. This prototype allows to estimate value and costs generated from a deployable solution and makes the value more tangible. This prototype requires initial investments, which should, however, be limited and reasonable and are also considered standard process steps in larger and cost intense initiatives.
37	Arguing with benefits and successful Analytics use cases to leadership to motivate investments and create commitment	Investments in the data Foundation and resources usually do not directly return on their investments without specific use cases and initiatives to develop Analytics solutions for the use cases. Further, value from Analytics solutions can be uncertain and be perceived as intangible. Thus, achieved benefits and successful use cases are used to motivate investments and create commitment. This can be addressed by potential use cases, which are promising to create value for the organization, or expressed needs from business units, which cannot be fulfilled under the current conditions. The specific use cases create a more motivating understanding for the potential return from investments for the sponsors.
38	User-focused and oriented delivery of developed solutions to create acceptance and increase use of deployed solutions	The delivery of the Analytics solution is focused on the users and oriented towards their acceptance and understanding of the solution. This includes generally pro-active transparency towards the user, explanations in business terms the users are used to, if possible the use of non-blackbox methods, of which the user can comprehend the behavior, addressing their questions, and, very importantly, explanations on how the users' input contributed to the solution. Further, if the users have the time and interest (usually missing for leadership roles), analytical steps taken are explained in detail. This approach recognizes that the users are the key to exploit the value of the solution by using it in the business process. Thus, by focusing on their acceptance and understanding, the use of the solutions for their value is more likely.
39	Employees receive feedback, training and are familiarized with code of conduct on data quality to improve data quality	Data Quality of manual data entries is addressed by creating a code of conduct for it and familiarizing employees with it. Further, in accordance with the code of conduct, trainings are provided, and the data quality of manual data entries are feedbacked. Thus, employees become aware of the issue and the responsibility on their end and reduce errors.

40	Collaborative field and forum approach of analyst and business users during solution development for improved collaboration to raise acceptance	The field and forum approach is a form of collaboration in which Analyst and business users collaboratively work in the focal business process, while the Analyst takes an observant and task assisting role. The Analysts gains understanding of the users' behavior, their requirements, and their use of information in the process, the process particularities, the data creation, the meaning of data and the use of data in the process as well as how an analytical solution can provide value. This increases the understanding of the Analysts, which contributes to easing the solution development, the handling of data quality issues and addressing users' needs, and results in more fitting solutions. The users build trust and acceptance in Analysts and in the developed solutions.
41	Automating solution are focused on increasing the value-addition from affected to reduce their fear and create acceptance	Analytical solutions developed to eventually automate process steps and users' activities focus exclusively on increasing the users' value-addition. This includes the automation of time-intense non-value adding activities (saving users' time), the creation of new capabilities of the users and the allocation of new responsibilities to the users. Users are pro-actively explained how their roles is changing and how their contribution to the organization will remain. This specific focus of automation is supposed to reduce their fear of losing their value-addition to the organization and increase their acceptance.
42	Guided ideation workshops in business functions to identify Analytics use cases	Specific ideation workshops guided experts in Analytics in business functions are used to identify and evaluate use cases for Analytics solutions in the business functions. While in the first part the quantity of ideas is most important, the second part is supposed to sort out by quality of ideas. This way, promising use cases which hold value for the business function are supposed to be identified and solutions can be developed subsequentially.
43	Include Analytics solutions in standard operating procedure to encourage use of solutions	The use of Analytics solution is, if possible, included in the workflow of the users and specific interaction of the user with the solution is required. Thus, users are getting familiar with the solution related to their tasks, can experience the value from it and build acceptance.
44	Formal and informal communication of benefits and value achieved with Analytics to present tangible value, build acceptance and reduce skepticism	Several forms of formal and informal communication and exchange on the value of developed Analytics solutions and successful initiatives can be arranged. This includes workshop, presentations, inside conferences and events (and the conversations afterwards), internal communication material, intranet sites, internal and external awards or business lunches. Besides Analysts itself, a presenting beneficiary of Analytics from the organization can underline the relevance. The intend of this communication is promotional and not educational in the first place. Hence, acceptance is created, and skepticism addressed by presenting tangible and realized value from Analytics in the organization. However, reluctant and unwilling employees may not attend anyway.
45	Involvement of Analysts in product/process design to improve data foundation	The designated data collection in designed processes and product designs may be intended for other reasons than Analytics and, thus, not provide data in a relevant format for Analytics solution development. The inclusion of Analysts into the design process for future products and processes can resolve these issues. Thus, the data foundation is improved.

46	Scheduled long-term evaluation of Analytics solutions to ensure the functionality and success of the solution and check the realization of the use	In the finalization of the Analytics initiative and solution development, long-term evaluation of the initiative's success is scheduled. In the long-term, the functionality and the need for adjustment is checked. The success is checked such that it might be used as promotional success to communication internally and build acceptance. Further, it is checked whether users have been willing and able to use the solution and adjustments must be made.
47	Development of consumable and visually meaningful Analytics solutions to motivate use and build acceptance	Analytics solutions must be developed with a user interface consumable for the intended users' role and with visual meaningful design, such that the relevant information and patterns can be understood easily. Resultingly, there may not be generalizable rules of consumability as well as not every single user's requests should be regarded. For that matter, insights might be presented in narratives, uncertainties in solutions need to be expressed, and previous solutions interfaces, to which the users are used to, might be used as blueprint. This motivates the user to be willing and acceptive to use the solution as well as to understand it.
48	Consistent consolidation of IT systems to reduce heterogeneity of IT systems and data inconsistencies	Since a single-source-of-truth is technically complex to achieve or to hold for organization and uncertain in its cost-efficiency when traversing from a very heterogenic systems landscape, organizations take steps to stepwise converge to it. One way to do so, is to constantly consolidate small numbers of IT systems to one once after another. This way, the number of IT systems and inconsistent data structures are constantly reduced over time and, thus, inconsistencies in data are reduced. This approach is especially used for systems that come of age or systems with redundant functionality exist.
49	Consistent integration of IT system to platform as integration layer to align data and reduce data inconsistencies	Since a single-source-of-truth is technically complex to achieve or to hold for organization and uncertain in its cost-efficiency when traversing from a very heterogenic systems landscape, organizations take steps to stepwise converge to it. One way to do so, is to use a platform solution as data integration layer and connect IT Systems one after another to the platform such that data can be interchanged between systems and platforms and thus between systems. Thus, inconsistencies in data are reduced. This approach is especially used to align systems with different functionality.
50	Consistent transition to modular IT system to reduce data inconsistencies and sustain consistency of data	Since a single-source-of-truth is technically complex to achieve or to hold for organization and uncertain in its cost-efficiency when traversing from a very heterogenic systems landscape, organizations take steps to stepwise converge to it. One way to do so, is to consistently transition to an IT system landscape (or eco-system) that is modular and allows a plug-and-play-style integration and detachment of systems. Thus, the consistency of data is not compromised by the exchange of systems. This approach is especially used for landscapes with expected changes and replacements of IT systems with heterogeneity needed to provide IT systems structures for unique processes that otherwise require extensive customization of systems.
51	Technical integration with Supply Chain Partners with platform integration layer to overcome technical challenges	To technically integrate a usually diverse and large amount of Supply Chain Partners with likewise diverse IT systems, a platform layer between focal organization and Supply Chain Partners is created. This way, the integration effort is reduced since the partners are on-boarded to the platform, which is supposed to be able to handle technical integration faster and easier than the IT landscape of the organization.

52	Pre-Check of available data before initiating Analytics solution development to increase chances of successful initiative	As criteria in the prioritization of initiatives and to ensure data issues will not break the initiative in the middle of solution development, a pre-check of the data intended to be used is conducted. This includes data quality, availability and fit of characteristics needed for the analysis. An unsuccessful pre-check should result in recommendations that allow to execute the initiative in the future.
53	Pre-check of process stability, flexibility and standardization to increase chances of successful deployment of Analytics solutions	Certain process conditions including its stability, flexibility and standardization can omit the analysis of data as well as omit the successful deployment of Analytics solutions, since relevant information cannot be provided. As criteria in the prioritization of initiatives and to ensure these issues will not render the solution as useless, a pre-check of the process is conducted. An unsuccessful pre-check should result in the design of process improvements (which might already resolve the need for an Analytics solution).
54	Pro-active involvement of workers council on intended solution development of human involved processes to reduce worries and create acceptance	Workers councils as representatives of the employees of an organization are usually concerned with the well-being of the employees including their fear of losing jobs and tasks to automation as well as being monitored. Pro-actively involving workers councils in the design of development processes of Analytics solutions that address human involved processes makes it possible to address concerns of the employees and provides transparency necessary for acceptance. If a solution development process is admitted by the workers council, employees' acceptance and willingness to cooperate can increase and their worries be reduced.
55	Set up of research consortium to co-fund solutions and solve complex Analytics problems	Research consortiums allow co-funding solutions, share risks and provide various perspectives and capabilities on complex analytics problems. Especially funding can sometime be increased by governmental funds that are intended to co-fund research and development projects. Eventually, these aspects create a stronger momentum of the Analytics solution development and improves the chances to successfully conclude the complex solution development, even if involved organization partially lack the analytics resources and capabilities. As opposed to contracting Analytics providers, the solution development remains in the organization and perceives a higher acceptance from the workforce.
56	Analytics solution development and deployment is cloud-hosted to ensure functionality	Due to heterogenic IT systems, the conditions on solution development may not be recreated for solution deployment. By hosting a development environment in the cloud, which can subsequently be used as deployment environment, the functionality of the solution is improved. Since the technical requirements are eventually fulfilled by the cloud server instead of users systems, the solution might run better. Due to the flexible use on the cloud resources, the cost may be less. Sensitive data may not be analyzed this way if the cloud is provided externally.

57	Habituation of users to Analytics solution to build acceptance, create understanding and test correctness of solution	A habituation of the users to the solution – a slow increase of users' interaction with a solution – is used to not shock the users with the solution and gain their collaboration. This way, the users are only partly asked to use the solution, or the solution runs without being used. Not using the deployed solution is intended to collect further insights on situations of decision-making, the solution cannot surpass human experience and to check the correctness of the solution in real processes. Further, the made decisions of the users can be compared to the recommended decisions by the solutions in form of a benchmark or shadow forecast, which presents the benefit of applying the Analytics solution to the users to gain their acceptance and understanding of how the solution would assist them. While this is not intended to make them look bad, the effect is a risk of this approach. Partly deploying a solution intends to exploit a slow and stepwise scaling for the purpose of showing benefits and building acceptance as well.
58	Identify Business owned tools/ Shadow IT and the analytical needs solved with them to identify use cases for Analytics solutions	The usually non-standardized business owned tools and Shadow IT in the business units are clear and present needs of the users for data, information and analytical insights. Identifying them provides the opportunity to offer standardized Analytics solutions to the users for their needs in accordance with organizational IT and data structure, data flows and analytical correctness. The resulting solutions, which should be superior to the business owned tools, create acceptance in the Analytics resources and their solutions such that the development of new business owned tools is depleted.
59	Using external Analytics resources as extended workbench to overcome shortage of Analytics resources	While the analytical resources are built up, are not available on the market or are under a demand peak, a way to increase availability of analytical resources is to use external providers in the solution development process. Since the solutions will potentially need long support, a collaborative development is still required to ensure long term functionality of the solution without repeatedly using the external provider.

Managing Supply Chain Analytics

This doctoral thesis seeks to contribute to research on the managerial aspects of Analytics in the field of Logistics and Supply Chain Management by conducting four individual research studies and an extensive synopsis of their results. The goal of this thesis is to provide managers in Logistics and Supply Chain Management with means and insights to manage Analytics initiatives in their organizations successfully and impactfully. The four research studies investigate separate components of the management process of Analytics relevant to the research objective including contributing factors outside of Analytics initiatives influencing them, archetypes of common Analytics initiatives in Logistics and Supply Chain Management, the value contribution of Analytics initiatives to the competitive advantage of organizations as well as barriers against impactful Analytics initiatives and measures against these barriers. Combined with an additional investigation of 15 process models of conducting Analytics projects and initiatives, the insights of the individual studies are mapped to process phases of Analytics initiatives.