Digital Transformation of Supply Chain Management – Challenges and Strategies for Successfully Implementing Data Analytics in Practice

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ABSTRACT

Digital transformation has been a crucial endeavor for businesses for many years, with Supply Chain Management (SCM) standing out as an area with significant potential for enhancement through new technologies. Data Analytics (DA), in particular, presents numerous opportunities in this context. Nonetheless, the adoption of data-driven decision-making in SCM remains a challenge for many practitioners. This research paper conducts a thorough investigation into the obstacles encountered when integrating Data Analytics into SCM practices. Utilizing a qualitative research approach, the study gathers comprehensive insights from expert interviews, shedding light on the practical challenges organizations face in their digital transformation journeys. Drawing from the empirical evidence obtained through expert discussions and an extensive review of relevant literature, this paper offers both expert-recommended and theoretically grounded strategies to overcome the barriers to digital transformation in SCM. In total. seven key challenge areas are identified, such as issues with data integration and quality, organizational resistance to change, skills shortages among employees, and concerns about the opacity of AI systems and the trustworthiness of their outputs. The paper presents 22 specific recommendation strategies for the successful deployment of Data Analytics in SCM, including the use of explainable AI to enhance trust in analysis outcomes, showcasing successful internal and employee-centric use cases, establishing a Data Analytics function in a centralized, decentralized, or hybrid format, and creating a central role for data governance. By providing actionable strategies, this paper enriches the current knowledge base, aiding practitioners in overcoming digital transformation challenges and maximizing the benefits of Data Analytics in improving SCM efficiency and digitally transforming supply chains.

CCS CONCEPTS

• **Applied computing** → Enterprise computing; Enterprise information systems; • **Information systems** → Information systems applications; Decision support systems; • **General and reference** → Document types; Surveys and overviews.

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KEYWORDS

Data Analytics, Supply Chain Management, Digital Transformation, Data Literacy, Expert Interviews, Best Practices

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1 INTRODUCTION

In recent times, there has been a noticeable trend towards decreased stability and predictability within logistics and supply chain (SC) networks, leading to elevated risks and greater uncertainty in decision-making within supply chain management (SCM) [1]. Concurrently, the emergence of novel technologies, such as advanced analytics, offers promising opportunities for refining decision-making processes, streamlining operations, and ultimately enhancing overall supply chain performance [2]. Data Analytics in SCM involves leveraging sophisticated algorithms and models to derive valuable insights from extensive datasets, enabling companies to forecast future trends, identify potential risks, and make well-informed decisions [3]. This becomes particularly vital in today's dynamic and competitive business environment, where agility and informed decision-making are key to a company's success.

Fortunately, the wealth of available data presents a significant opportunity to mitigate uncertainty. However, realizing the full potential of Data Analytics, including predictive and prescriptive analytics, faces challenges stemming from a lack of understanding regarding their practical applications and performance benefits, as well as a shortage of implementation expertise [4]. This challenge is particularly pronounced for smaller entities such as SMEs or in smaller countries with limited human resources. For example, in Austria, characterized by a strong presence of small and medium-sized enterprises (SMEs), the integration of Data Analytics into SCM processes is still nascent. Despite recognizing the potential of these technologies, their actual implementation remains limited, with research often confined to theoretical analysis [4–6]. This underscores a notable research gap, as understanding the specific hurdles and opportunities associated with deploying Data Analytics in SCM within the Austrian context can provide valuable insights for both industry practitioners and researchers, with potential applicability to similarly sized economies [7]. Consequently, this paper aims to explore the utilization of Data Analytics in SCM in Austria, focusing on current implementations and the challenges therein. Through this exploration, it seeks to enrich existing knowledge and offer actionable recommendations for companies aiming to harness Data Analytics in their SCM operations.

With the above considerations in mind, this study addresses the following research questions:

- RQ1: What are challenges and obstacles in the context of implementing Data Analytics in SCM practice from experts' point of view?
- RQ2: What are best practices and action strategies to handle challenges in the context of implementing Data Analytics in SCM practice from experts' and literature perspective?

The answers to these inquiries will not only shed light on challenges and obstacles when implementing Data Analytics in SCM Austria but also identify best practices and strategies to deal with these challenges and facilitate wider adoption of Data Analytics in SCM. This, in turn, can inform future research endeavors and industry practices in this domain, contributing to the advancement of SCM. The subsequent sections of the paper are structured as follows: Section 2 provides the theoretical framework underpinning the study. Section 3 outlines the research methodology employed. In Section 4, the study's findings are presented. Subsequently, Section 5 concludes the paper, highlighting limitations and outlining potential avenues for future research.

2 BACKGROUND

Subsequently, the two concepts underlying the paper, i.e., Data Analytics (DA) and Supply Chain Management (SCM) are explained.

2.1 Data Analytics

Data Analytics represents a multifaceted domain that transcends traditional data analysis by not only processing data through established methods but also by seeking to provide a deeper, actionable insight into the data itself. While data analysis focuses on extracting useful information through conventional techniques such as statistical, empirical, or logical theories, Data Analytics delves further into the theories, technologies, instruments, and processes aimed at understanding and exploring data in a way that actionable insights can be derived [8]. At its core, Data Analytics is an interdisciplinary field that leverages computer systems for the analysis of large datasets, supporting decision-making processes. It borrows elements from a wide range of scientific disciplines, including statistics, signal theory, pattern recognition, computational intelligence, machine learning, and operations research. This interdisciplinary approach underlines the comprehensive nature of Data Analytics, highlighting its role in integrating diverse methodologies for the thorough examination of data [9].

Semanjski (2023) describes Data Analytics as the science of merging heterogeneous data from multiple sources, establishing relationships and causal links, making predictions, and ultimately, facilitating informed decision-making. This definition emphasizes the importance of integrating varied data sources and the analytical process in drawing meaningful conclusions that support strategic decisions [10].

Delen and Demirkan (2013) frame Data Analytics as a means to achieve business objectives through the detailed reporting of data, trend analysis, predictive modeling for forecasting future challenges and opportunities, and the analysis and optimization of business processes. This perspective underscores the practical application of Data Analytics in a business context, where it serves as a tool for enhancing organizational performance by leveraging data-driven insights [11].

Sun et al. (2017) further elucidate the role of Data Analytics in business decision-making, highlighting its capacity to analyze current problems and future trends, create predictive models, and optimize business processes based on historical or current data. This approach is geared towards improving organizational performance by making informed decisions rooted in comprehensive data analysis [12].

In summary, Data Analytics is characterized by its comprehensive, interdisciplinary approach to data examination. It extends beyond mere data processing to include the application of diverse theories and technologies aimed at generating actionable insights. Through the fusion of heterogeneous data, establishment of relationships, predictive modeling, and process optimization, Data Analytics empowers decision-making and enhances organizational performance across various domains.

2.2 Supply Chain Management

A supply chain (SC) constitutes a complex network of entities collaborating to produce and distribute a product, along with its associated information such as pricing and delivery schedules, to the final consumer. It encompasses all entities engaged in the process of value generation related to the creation of products and services, capturing the entirety of activities and procedures applied to a product from its inception to its final delivery. Specifically, a supply chain initiates with the manufacturer of raw materials and concludes with the delivery of the finished product to the consumer. Supply Chain Management (SCM), as conceptualized by Mentzer et al. in 2001, involves the deliberate and strategic coordination of traditional business activities and strategies within and across companies in the supply chain. This coordination aims to enhance the long-term efficiency of both individual companies and the supply chain collectively [13].

The primary objective of SCM is to fulfill consumer demands in the most efficient manner possible, necessitating the refinement of numerous internal and external processes involved in value creation. The evolution of SCM has witnessed a shift from focusing on the optimization and integration of internal processes during the 1990s to emphasizing enhanced information sharing and cooperative management of intricate value-creation activities in the 2000s. A key aim has become the alignment of both internal and external supply chain operations [14].

Numerous studies have explored the specific responsibilities and processes within SCM, indicating a variety of critical activities. For instance, Lambert and associates identify eight essential SCM activities [15], Chopra and Meindl outline fifteen activities across three main supply chain macro-processes [16], the SCOR model details six primary processes along with several sub-processes [17], and Porter's value chain model lists six main activities [18].

Consequently, this study delineates SCM into five principal activities: procurement, production planning, warehouse management,

Table 1: Participants of the Expert Interviews

ID	Industry	Expert Status
1	Building industry	SCM process designer analyst; 8 years experience.
2	Automotive industry	Logistics and SC manager; 10 years experience.
3	Manufacturing industry	Head of Demand Chain for several years; 11 years experience.
4	Metal industry	Head of Data Analytics; 6 years experience.
5	Mechanical engineering	Head of Global Operations Excellence; several years experience.
6	Food retail company	Head of SCM Monitoring & Analytics; 10 years experience.
7	Mechanical engineering	Head of SCM with focus on production logistics; 10 years experience.
8	Paper industry	Purchasing manager, including all SCM tasks; several years experience.
9	Manufacturing industry	Manager in SCM Operations & Performance, 13 years experience.

logistics and transportation planning, and demand management, serving as the foundation for expert interviews and further analysis.

3 RESEARCH METHODOLOGY

To address the defined research questions, qualitative expert interviews serve as an appropriate method. The objective of these interviews is to explore the challenges associated with Data Analytics within Austrian SCM practices. Expert interviews are particularly well-suited for delving into tacit knowledge within a specific domain, a characteristic evident in this study [19, 20]. Specifically, the focus is on identifying: i) the challenges and obstacles encountered before and during DA implementation and ii) the collection of best practices and action recommendations for handling these challenges and obstacles. The essential steps of expert interviews encompass: 1) expert identification and selection, 2) data collection, and 3) data analysis. In this study, an information-based selection approach is adopted for expert identification and selection [21]. Experts are chosen based on predefined criteria, including: i) extensive practical experience in SCM (over 5 years), ii) current involvement or leadership in SCM analysis tasks, and iii) comprehensive management-level comprehension of Data Analytics' application in SCM (over 3 years of company experience). The search for suitable candidates was facilitated through contacts at the Logistikum, the leading research institution in logistics and SCM in Austria, providing access to a wide network of corporate partners [22]. A total of 9 experts from large companies were interviewed, with details anonymized as per the experts' request (cf. table 1).

Data collection follows a semi-structured interview guide, enabling interviews to unfold naturally while ensuring consistency through standardized questions across each interview, albeit potentially in varying sequences [23]. The interview guide was distributed to participants via email at least one week before their scheduled interview. Interviews were conducted either face-to-face or via video conference using MS Teams. Each session was recorded and subsequently analyzed directly from the recordings [24, 25].

4 RESULTS

The results of the expert interviews reveal a total of seven main challenges in the context of implementing DA in SCM practice. For each main challenge, best practices from experts' point of view and as defined in relevant scientific literature are presented as well.

4.1 Organizational integration and role definition

Regarding the proper organizational integration of Data Analytics and the corresponding definition of roles and responsibilities, experts provide several recommendations. Expert 4 mentions the establishment of a separate unit as critical to success. Due to frictions with controlling, there were internal fears or uncertainties about the difference between reporting and Data Analytics. To actively address these fears, the analytics staff position was directly linked under the CFO (Chief Financial Officer). This ensures maximum transparency at the management level and allows operational responsibilities to be uniformly and clearly delineated. The establishment of a separate analytics unit is also recommended by Expert 7 as an organizational integration approach. This approach is also presented in the literature as a possibility, specifically mentioning areas such as controlling or IT. Another option is to depict Data Analytics in a decentralized manner, i.e., integrating a group of data scientists into different areas. A hybrid combination, i.e., connecting a central analytics unit with decentralized positions, is mentioned in the literature as an approach [26]. In the case of decentralization, at least the establishment of a steering group is recommended in the literature, consisting of representatives from different areas. The task of this group is to monitor and jointly coordinate all analytics activities [27]. Another challenge in this context is to define the right roles and responsibilities within the analytics team or the organization. Expert 4 identifies three key roles: Data Analyst, Data Scientist, and Data Engineer. These role profiles are also mentioned in the literature as the central roles in the Data Analytics context [28]. Additional roles, e.g., Data Architect or Data Consultant, are also mentioned [29]. In general, experts also name the active support of organizational changes in the context of building an analytics structure through active change management as a factor of success, which is also consistent with relevant literature [30, 31].

4.2 Lack of sufficiently qualified employees

Regarding the shortage of sufficiently qualified employees, Expert 2 considers the connection between domain experts and data experts as important. In the future, there will be an increasing need for the integration of both skills, i.e., at the process level and at the algorithm level. The ability to think integratively, or to combine knowledge from the management area with knowledge in the context of data analysis, is also seen in the literature as essential for the future [32]. Expert 4 mentions in the context of dealing with a lack of skills in the Data Analytics area, the collaboration with research institutions as an important element. Contrary to cooperation with consultants, he stated that actual state-of-the-art knowledge can be conveyed and developed within the framework of solid research projects. Expert 6 also mentioned the intensive cooperation with universities of applied sciences and universities as a recommendation for action in connection with the shortage of data science professionals in the market. This form of cooperation not only enables access to know-how but also allows the company to potentially recruit future employees in the form of students early on [33]. Expert 9 also mentioned collaboration with external partners as an important step to deal with a lack of internal competencies. Specifically, he stated that the company in question could not and did not want to become an AI organization in the future, and therefore the only possible way to build knowledge was through external partners and the use of existing AI software.

4.3 Silo thinking and a lack of overarching understanding of data and Supply Chain

In relation to silo thinking and a lack of cross-functional data or SC (Supply Chain) understanding, Expert 2 recommended the cooperation between operational and tactical decision-makers as a course of action. Only when decisions are considered cross-functionally can we move away from thinking in terms of areas and silos. The ability to move from the problem and its implications in other areas to the specific, cross-functional data needs was also named as central. Expert 5 pointed to the increased use of cloud infrastructure as a way to efficiently deal with data from various sources in the context of an overarching data structure. Expert 8 also identifies thinking in organizational silos as a challenge. Even if on paper, or at the data level, all boundaries between areas seem to be eliminated, these boundaries must also be dismantled in the minds of the employees, which is significantly more difficult. A lack of basic understanding of other SCM areas and processes in the SC is also seen by Expert 9 as an obstacle in the context of Data Analytics. Acting without a holistic understanding can prevent the best analytical results from being implemented or utilized. The challenge of lacking cross-functional and SC-wide thinking is also mentioned in the literature. This applies not only to the mindset of the employees but also to the datasets and their linkage. Specifically, the collaboration or integration of experts from multiple areas is recommended in this context [34].

4.4 Lack of trust and low acceptance of AI black boxes

In the context of lacking trust and low acceptance of AI black boxes, experts have mentioned the representation of uncertainty ranges of forecasts as a way to better understand AI results. The integration of Explainable AI (XAI) functions, e.g., feature relevance, was also recommended by the experts. This could strengthen trust in Data Analytics results and increase their transparency from the perspective of employees. The lack of trust in advanced data analysis or its results and the relevance of XAI is also clearly confirmed in the literature. Specifically, methods such as LIME (Local Interpretable Model-agnostic Explanations), SHAP (SHapley Additive exPlanations), or CEM (Contrastive Explanation Method) are mentioned as possible approaches for better transparency and explainability of AI results [35, 36]. In this context, the consideration of legal aspects, e.g., in connection with the AI Act of the European Union, is becoming increasingly central. Here, besides transparency in the decision-making process, the comprehensible documentation of Data Analytics results and the data used therein plays an important role [37].

4.5 Limited room for maneuver due to dependence on Group structure

Regarding the limited scope of action due to dependency on corporate structures, the experts do not mention any specific recommendations for action. The literature mentions the importance of top management support at the national level [38]. Only when local leaders support Data Analytics initiatives and communicate them accordingly to the corporate headquarters can the scope for action be expanded or can focused analytics initiatives emerge. Ideally, subsequent integrated projects take place, which are driven by the local unit but also considered and integrated across higher corporate levels.

4.6 Heterogeneous system landscape, interface, and data quality problems

In the context of heterogeneous system landscapes, interface and data quality issues, Expert 6 mentions the reduction of input options in data entry and maintenance as a possible measure to improve data quality. Specifically, this should prevent incorrect or abnormal inputs or at least alert users to unexpected value ranges. Also, an overarching data mapping, especially in the context of old and new systems, is named as a critical success factor. These recommendations are also found in the literature, e.g., in terms of overarching data architectures and data governance initiatives [39]. Additionally, the implementation of central roles that have an overview of all data structures and their connections within the company and maintain them sustainably is cited as a recommendation for action. Here, the literature mentions e.g., the following roles: Executive Sponsor, Data Governance Leader, Data Owner, Data Steward, Data Governance Council, Data Governance Office, Data Producer, and Data Consumer [40, 41].

4.7 Lack of awareness of potential and difficult internal marketing

Regarding the lack of knowledge about the specific potential of Data Analytics and the difficulty of internally marketing such analytics initiatives, experts particularly mention demonstrating the added value in daily use. Only if this value is visible and can be generated without disproportionately high additional effort, would such approaches be utilized or demanded. Here, the continuous and systematic integration of the analytics department into decision-making processes of different SCM areas is also mentioned as critical to success. Expert 6, in the context of unrealistically high expectations from Data Analytics at the management level, mentions illustrating the complexity of problems and data as a means of

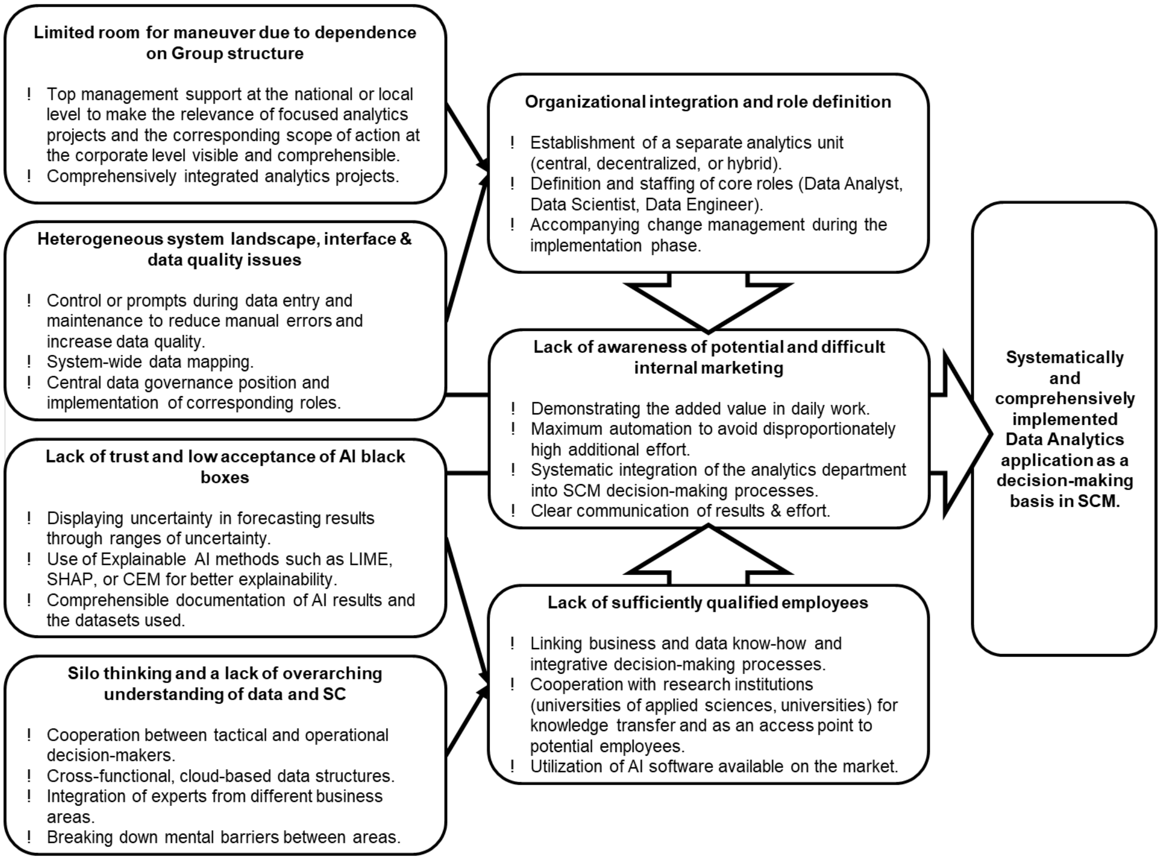

Figure 1: Summary of Challenges, Best Practices and Strategic Recommendations for Implementing Data Analytics in Supply Chain Management

better communicating such approaches. Subsequently, this could also create a realistic expectation regarding the results and effort of analytics projects. These points are also found in the literature, where, for example, the lack of understanding of AI applications, their potential, and the required effort is cited as critical [42].

5 SUMMARY, CONCLUSION AND OUTLOOK

In summary, the experts mention seven main challenges and 22 best practices respectively strategic recommendations to deal with the challenges of implementing Data Analytics in SCM practice. The following figure provides a summary of the challenges and the recommendations derived based on experts' input and literature:

In conclusion, our extensive research through expert interviews and literature analysis has illuminated the multifaceted challenges and best practices for the implementation of Data Analytics within Supply Chain Management (SCM). Organizational integration and role definition have emerged as pivotal, with a separate analytics unit underlined as a cornerstone for successful implementation, ensuring transparent delineation of operational responsibilities. The essential roles of Data Analysts, Data Scientists, and Data Engineers have been identified, accompanied by the necessity for active change management to support organizational transitions. The acute shortage of sufficiently qualified employees is mitigated by fostering cooperation between domain experts and data experts, highlighting the increasing necessity for integrative thinking. Partnerships with educational and research institutions have been identified as a strategic resource for knowledge transfer and talent acquisition. The issue of siloed thinking has been addressed through the advocacy for cross-functional cooperation and cloud infrastructure to efficiently manage diverse data sources. The importance of an overarching understanding of SCM processes has been accentuated, alongside the dismantling of mental barriers to foster a collaborative and informed analytical environment. Trust and acceptance of AI within organizations have been tied to the clarity provided by Explainable AI (XAI) techniques, which elucidate the decision-making processes and forecast uncertainties. Legal considerations, particularly the EU AI Act, are increasingly influential, emphasizing the need for transparency and comprehensive documentation of analytics and data. The limited room for maneuver due to corporate dependencies underscores the need for top management support, with local leaders playing a crucial role in expanding the scope of action and endorsing analytics initiatives. Heterogeneous system landscapes pose significant challenges; however, recommendations such as reducing input options and system-wide data mapping, along with the establishment of central roles for data governance, have been suggested as mitigative measures. Lastly, a lack of awareness of the potential of Data Analytics and its internal marketing challenges points to the need for making tangible benefits visible in daily operations, without imposing undue effort, thus fostering realistic expectations and broader utilization.

In summary, the effective implementation of Data Analytics in SCM requires a holistic approach that encompasses strategic organizational structure, skilled personnel, integrative thinking, trust and transparency, legal compliance, and the acknowledgment of the potential and practical benefits of such initiatives.

This study, while comprehensive, encounters several limitations that warrant acknowledgment. Firstly, the insights gleaned from expert interviews, although valuable, are subject to the inherent biases and perspectives of the individuals. These experts' experiences, while extensive, may not fully represent the diversity of challenges and best practices in the broader field of SCM. Secondly, the rapid evolution of technology means that the current findings might soon be outdated, given that the field of Data Analytics and AI is continuously advancing. The tools and methods considered state-of-the-art today may be superseded by more advanced solutions soon. Another limitation is the focus on larger organizational structures and the potential neglect of small and medium-sized enterprises (SMEs), which may face distinct challenges not addressed in this study. Additionally, the legal and ethical considerations highlighted, particularly in relation to the EU AI Act, are region-specific and may not apply globally.

Practically, this research illuminates the challenges in the context of Data Analytics applications within SCM for smaller nations, offering a blueprint for organizations in similar environments to pinpoint and act on key operational domains as guided by the action recommendations provided. Future explorations could expand upon this work, conducting parallel studies in varied national contexts and with more extensive expert panels, to juxtapose and enrich the understanding gleaned from this study's outcomes.

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