

Association for Information Systems

## AIS Electronic Library (AISeL)

---

ICIS 2022 Proceedings

Data Analytics for Business and Societal  
Challenges

---

Dec 12th, 12:00 AM

### Data Analytics for Effective Decision-Making in Crises - Identifying Relevant Data Analytics Competencies for Automotive Procurement Departments

Sven Klee

*Universität Kassel, sven.klee@wi-kassel.de*

Andreas Janson

*Institute of Information Management, andreas.janson@unisg.ch*

Follow this and additional works at: <https://aisel.aisnet.org/icis2022>

---

#### Recommended Citation

Klee, Sven and Janson, Andreas, "Data Analytics for Effective Decision-Making in Crises - Identifying Relevant Data Analytics Competencies for Automotive Procurement Departments" (2022). *ICIS 2022 Proceedings*. 2.

[https://aisel.aisnet.org/icis2022/data\\_analytics/data\\_analytics/2](https://aisel.aisnet.org/icis2022/data_analytics/data_analytics/2)

This material is brought to you by the International Conference on Information Systems (ICIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in ICIS 2022 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact [elibrary@aisnet.org](mailto:elibrary@aisnet.org).

# Data Analytics for Effective Decision-Making in Crises - Identifying Relevant Data Analytics Competencies for Automotive Procurement Departments

*Completed Research Paper*

**Sven Klee**

Information Systems,  
University of Kassel  
Pfannkuchstr. 1,  
34121 Kassel, Germany  
sven.klee@wi-kassel.de

**Andreas Janson**

Institute of Information Management  
University of St.Gallen  
Müller-Friedberg-Strasse 8,  
9000 St.Gallen, Switzerland  
andreas.janson@unisg.ch

## Abstract

*Crises become the norm for organizations, as recent years have shown. Especially the automotive industry is still facing disruptive changes such as e-mobility, connected cars or autonomous driving. Disrupted supply chains, related production downtimes and associated financial losses are consequences. Procurement departments are the interface between internal and external stakeholders in supply chains, and therefore, the central authority for managing crises. In such situations, effective decision-making is essential. Positive effects of data analytics on decision-making were part of numerous research endeavors, as well as related data analytics competencies. We conducted semi-structured interviews with experienced experts about relevant data analytics competencies in procurement departments. We present an overview specifically for procurement departments and derive implications of these competencies on decision-making. As a result, we apply our findings to existing research from a theoretical perspective and support procurement leaders and their departments in facing current and future challenges from a practical perspective.*

**Keywords:** Data Analytics Competencies; Decision-Making; Procurement

## Introduction

“The role of procurement is changing. Value chains are becoming more complex, with increased risks and opportunities that accompany the complexity, developments in digitization, automation and analytics that unlock previously untapped potential [...]” (Ahuja and Ngai 2019). Billions in costs due to additional tariffs concerning the Brexit, customs costs at American and Chinese borders due to the trade war, costs caused by stopped productions with regard to force majeure, lack of semiconductors, or COVID-19 illustrate the impacts of external effects and clarify the increasingly complex, more volatile, and more risky procurement responsibilities (Ahuja and Ngai 2019). The current war in Ukraine once again highlights the vulnerability of global supply chains and organizations are facing another supply shortage. Organizations lost an average of \$182 million in revenue caused by supply disruptions (Interos Report 2022). Thus, supply disruption risks are one major challenge for procurement departments (Dhurandhar et al. 2015; Wang et al. 2015; Xiang 2014). The automotive industry in particular is already facing massive challenges, such as autonomous driving, connected cars, or e-mobility, and has to manage increasingly volatile supply chains as an additional challenge (Gao et al. 2016; Hanelt et al. 2015; Simonji-Elias et al. 2014). There are several

approaches to facing these challenges regarding uncertainty and supply chain vulnerability. One approach is to use data analytics to minimize uncertainty and, based on this, to improve decision-making reliability in times of crisis. Numerous studies have shown that the effective use of data can lead to significant added value in organizations (Chae et al. 2014; Chen et al. 2012; Olszak and Zurada 2019). In this context, however, relevant data analytics competencies of individuals are needed to ensure such an effective use of data (Liberatore and Luo 2013; Persaud 2020; Shuradze and Wagner 2016), especially in crisis situations. In terms of organizational structures, procurement departments can be seen as the central interface between internal and external stakeholders, which also highlights the relevance in the overall corporate management of crises (Pellengahr et al. 2016). Many research approaches have already addressed the study of data analytics competencies (Ghasemaghahi et al. 2018; Gorman and Klimberg 2014; Klee et al. 2021), and therefore numerous approaches and concepts are available as adequate starting points. To account for a contextualization of data analytics competencies, we take up these existing research results and examine which data analytics competencies buyers in procurement departments should have according to experienced experts by conducting semi-structured interviews. These data analytics competencies are intended to help organizations to better manage crises with data-based decision-making. Building on this, we also focus on the generalizability of the analyzed data analytics competencies. By expanding relevant data analytics competencies, we also see potentials for pushing data analytics in organizations and, thus, also for overcoming other challenges beyond crises. This is based on the thesis that data analytics can improve decision-making in crises, and that constantly new insights and their adaptation can result in increased resilience and sustainable effects (Burnard et al. 2018). Therefore, we address the overarching research question (RQ):

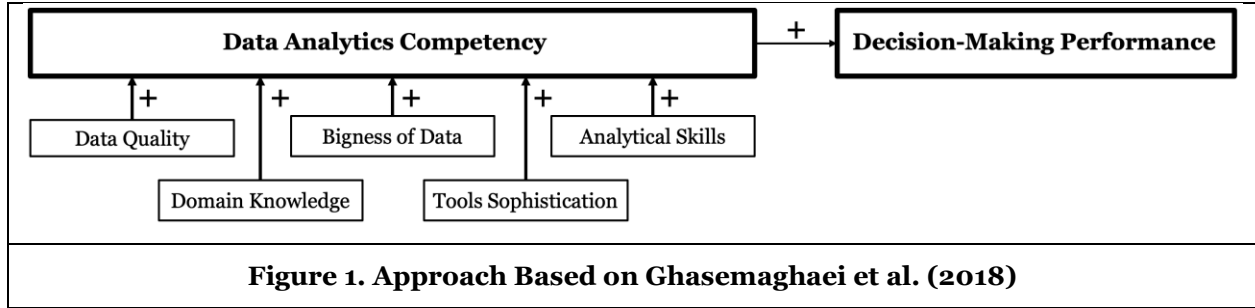
*RQ: What are relevant and generalizable data analytics competencies in procurement departments to improving decision-making in crises situations and what valuable implications can arise from this?*

To address this research question, we start with a theoretical background in the following section by addressing the defining aspects of data analytics competencies and highlight how the framework from Ghasemaghahi et al. (2018) related to data analytics competencies and decision-making scaffolds the subsequent empirical study. We also present relevant approaches of data-driven decision-making and a positioning of our research in the context of these previous research results. Building on this, we discuss related work and highlight how our paper contributes to existing research. We further describe the conduction of our expert interviews in detail within the methodology section. In the discussion section, we analyze the results of the expert interviews and, in accordance with our research question, examine the data analytics competencies that are relevant for buyers in procurement departments. In this context, we also discuss similarities and differences with existing research in the field of data analytics competencies and derive theoretical and practical implications of our results on decision-making in procurement departments. The focus here is on practice-relevant propositions to assist procurement leaders and their departments. The final conclusion section summarizes our findings and discusses the limitations of our research.

## **Theoretical Background**

### ***Data Analytics Competency and its Implications for Decision-Making***

First of all, it is relevant to create an understanding of the term data analytics competencies for the purposes of this research paper. Competencies in general can be described as mainly forward-looking behavioral repertoires, while competencies are predominantly states of achievement (Kurz and Bartram 2008). In this context, competencies are the more appropriate term. Building on this, Chen et al. (2012) defined data analytics competencies as a coherent set of information technology, domain, and communication competencies. In the context of organizations, data analytics competencies can be described as the use and combination of data analytics resources for the purposeful analysis of data (Ghasemaghahi et al. 2018). Resources, however, can be divided into tangible organizational resources such as the physical information technology (IT) infrastructure, human IT resources such as management or technical IT skills, and intangible resources such as knowledge assets (Bharadwaj 2000). Based on this, Ghasemaghahi et al. (2018) derived a detailed definition of data analytics competencies by describing the five specific dimensions data quality, bigness of data, analytical skills, domain knowledge and tools sophistication as illustrated Figure 1.



Within this approach, data quality can be defined using four categories: intrinsic, contextual, representational, and accessibility (Wang and Strong 1996). Intrinsic describes the correctness of data with regard to specific contexts, whereas contextual describes the correctness of data independently of contexts, for example, with attributes like timelessness or relevance of data (Ghasemaghaei et al. 2018). Representational describes the data consistency and also an appropriate representation of a good understanding of the data (Ghasemaghaei et al. 2018). At last, accessibility describes the simplicity of data sourcing (Ghasemaghaei et al. 2018). The second dimension, bigness of data, describes the constantly growing availability of new data, which also continuously expands the possibilities of data analytics (Lycett 2013). Analytical skills and domain knowledge as further dimensions can be described together in this context as competencies that enable employees in organizations to generate added value from data by being able to identify the business background or problems in their domain (Sukumar and Ferrell 2013) and to use data analytics to positively influence decision-making based on data (Wong 2012). Finally, tools sophistication describes, on the one hand, the maturity and complexity of the technical expertise in organizations (Chwelos et al. 2001) but, on the other hand, also the functional scope of the tools for generating business insights (Gillon et al. 2014). With the help of their research, Ghasemaghaei et al. (2018) found out that the five dimensions above positively influence data analytics competency, and this in turn positively influences decision-making performance in organizations.

In this context, the more specific technical and managerial data analytics competencies are drivers of performance in organizations, where managerial competencies predominantly have a positive influence in small and medium-sized enterprises (Mikalef et al. 2019). Especially through empowerment of those employees with strong problem-solving competencies by top managers, significant potential can be exploited through analytics (Rialti et al. 2019). Furthermore, business analytics competency as a collective term for several techniques, technologies, systems, practices, methodologies, or applications for analyzing relevant business data can foster competitive advantage in organizations (Wang et al. 2019). At this point, the positive effects of several data analytics competencies in different organizational levels can be emphasized. Distinct data analytics competencies among employees, such as analytical domain competency, data management competency, or technical competency, have an impact primarily on business values within the operational areas but can also have a positive effect on higher-level activities at the organizational level or even beyond (Klee et al. 2021).

It is also highly relevant to clarify the understanding of roles in organizations. Business-oriented analysts, for example, need broad-based managerial communication and process skills, whereas full-time data scientists still need to have an understanding of the business processes but already need more pronounced technical competencies (Mauro et al. 2018). Technical experts like data developers or engineers are not considered further for our purposes with focus on procurement departments.

**Data-Driven Decision-Making in Crises Situations**

As with current research on data analytics competency, there is an increased interest in research on data-driven decision-making in crises situations, particularly as a result of the crises of recent years. Thus, there are numerous research foci and perspectives in this field. Countries, organizations and individuals are all part of a constantly changing environment that offers many opportunities for success and growth, but also increasingly threats and dangers (Burnard et al. 2018). Therefore, the search for ways to defy such threats is self-explanatory. One of many ways to defy such challenges is the use of data (Qadir et al. 2016). The overall goal of collecting and analyzing data is to improve decision-making, which can lead to massive

competitive advantages for organizations through faster, better and more accurate decisions (Farrokhi et al. 2020). In this context, resilience has repeatedly been a focus topic in many previous research approaches. Resilience describes the adaptation of a system following the effects of a disruption (Holling 1996). In the context of resilience, two important factors have received considerable attention in previous research. Preparation describes the degree to which an organization has developed a systematic approach to address crises reactively or proactively, while adaptation describes the degree to which resources are flexibly allocated, either rigid or agile (Burnard et al. 2018). Here, an important link to the overall goal of our research also becomes clear. We have emphasized that we want to focus primarily on generalizable data analytics competencies. These are basic prerequisites for the effective use of data analytics in organizations (Liberatore and Luo 2013; Persaud 2020; Shuradze and Wagner 2016). Especially in crises situations, quick and effective decisions are necessary in organizations (Burnard et al. 2018). As already explained, the automotive industry is facing a large number of major challenges in addition to past and current crises. We therefore focus on data analytics competencies and, due to the current situation, primarily consider crisis situations. Nevertheless, it must be noted that it is possible to achieve sustainable effects in organizations through preparation and adaptation. Especially in procurement departments as a central link between internal and external factors (Pellengahr et al. 2016), the situation remains challenging, which highlights the potential of data analytics and the existence of the necessary competencies for decision-making in crises situations.

**Positioning of this Study in Context of Related Work**

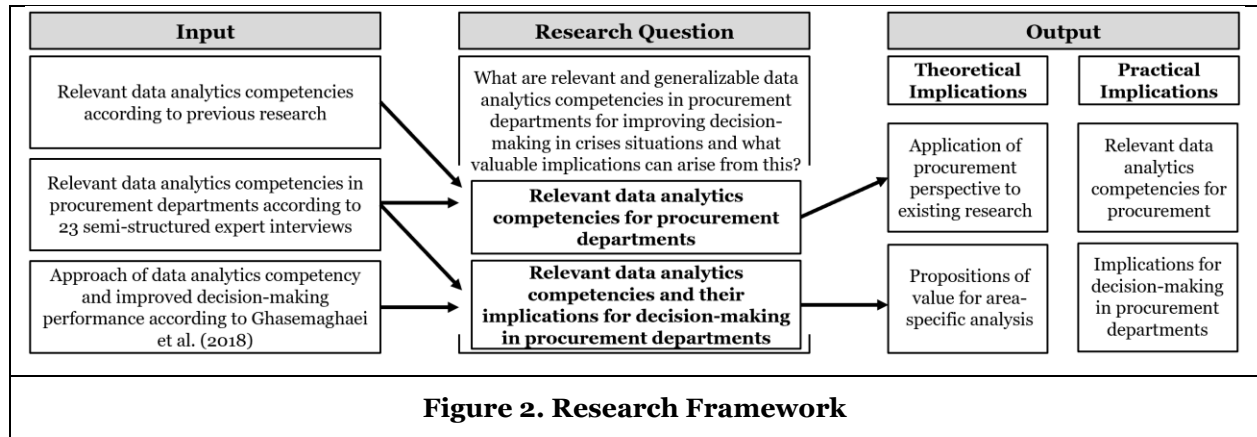
In crises situations, effective decisions are necessary and data analytics can contribute to this (Ahuja and Ngai 2019). However, procurement departments also need the necessary competencies to realize this, on the one hand, due to the central interface role of procurement departments in crisis situations and, on the other hand, also from a theoretical point of view regarding area-specific analyses of necessary data analytics competencies. In our research, we focus on relevant procurement-specific data analytics competencies with a focus on decision-making and facing crises situations. At this point, it is also of interest to what extent data analytics competencies identified in previous research, coincide with those we evaluate with the help of our expert interviews. Table 1 presents our research in conjunction with previous research approaches. The selected papers can be considered as a small sample and represent a range of different approaches to identify. We emphasize at this point that there is no claim to completeness. Due to the dynamic research in this fields, a fully comprehensive overview is not a valuable goal. Rather, we present a broad selection of different scientific approaches and perspectives.

<b>Selection of Previous Research on Data Analytics Competencies</b>	
Debortili et al. (2014)	Analysis of job advertisements for deriving relevant business intelligence and big data competencies
Ghasemaghaei et al. (2018)	Empirical analysis of competency dimensions and impacts on firm decision-making
Mauro et al. (2018)	Analysis of high number of job advertisements to gain clarity about relevant data-driven job competencies
Mikalef and Krogstie (2019)	Investigation of gaps between organizational skill needs and existing employee skills
Klee et al. (2021)	Evaluation of data analytics competencies from existing literature and expert interviews and impacts on business value in organizations
<b>Selection of Previous Research on Data-Driven Decision-Making in Crises Situations</b>	
Burnard et al. (2018)	Empirically exploration of decision-making under crises and disruption for building up organizational resilience
Farrokhi et al. (2021)	Analyzing the use of Artificial Intelligence for decision-making in crisis management
Qadir et al. (2016)	Evaluating big data and its use for improving crisis response by illustrating the history and future of crisis analytics
<b>Our research</b>	
<i>Evaluation of relevant and generalizable data analytics competencies in the field of procurement for improving decision-making in crisis situations</i>	
<b>Table 1. Related Work</b>	

## Methodology

### Research Framework

The described expert interviews represent the central component in our research framework, as procurement experts explain their experiences regarding necessary data analytics competencies. Furthermore, as already clarified in the explanation of the theoretical background, we build on the findings from Ghasemaghahi et al. (2018), who were already able to show how data analytics competency can positively influence decision-making. Existing research is used as another component for input. In the context of our central research question, we combine these input components in order to receive an overview of relevant data analytics competencies in procurement departments. Based on this, we also want to make statements about possible implications for decision-making in procurement departments. As an output, we aim to make both theoretical and practical contributions. From a theoretical perspective, we aim to use previous research results on relevant data analytics competencies and compare them with our procurement-specific perspective. Furthermore, we want to show that it can be valuable to investigate data analytics competencies specifically in individual business units. From a practical perspective, we first want to provide procurement leaders and their organizations with guidance regarding relevant data analytics competencies. However, we also want to show implications of these competencies for decision-making in procurement departments. Figure 2 summarizes our research framework by presenting our input items, the related research question, and the resulting output.



### Research Setting and Data Collection

As described in the introduction, crises and associated supply chain disruptions have become almost the norm in recent years. Procurement departments are an important control instance in interrelated supply chains. Based on this, we focus explicitly on this context. Especially in connection with data analytics as a tool to defy uncertainties, we see an exciting research field with great potential for new insights. In the area of data analytics competencies, we found that little research exists and therefore deliberately address this research gap. To answer our overarching RQ, we conducted 23 semi-structured interviews with experts. Contact with experts from consulting or data service companies as well as experts from technology companies were established through previous or ongoing data analytics projects. The experts from the automotive manufacturers were requested according to their responsibilities in the respective companies. It is important to mention that the technology companies, among other products, are direct suppliers for automotive manufacturers. All interviewees have a professional focus on data strategy, data analytics, or related topics such as business intelligence or similar. The experts' experiences are very diverse. The interviewees include managers who are responsible for the competencies of their employees, consultants who, among other things, develop strategies for necessary competencies, data scientists who regularly work with buyers and therefore know the relevant competencies, and representatives of software companies who work with data and the requirements for handling it. Table 2 summarizes the companies and their sizes to provide a better overview.

Company ID	Companies	Number of Employees
1	Automotive manufacturer 2	> 100,000
2	Software corporation	> 100,000
3	Engineering/Technology 1	> 100,000
4	Auditing/strategy consulting 1	> 100,000
5	Strategy consulting 3	> 100,000
6	Auditing/strategy consulting 2	> 100,000
7	Engineering/Technology 2	> 100,000
8	Engineering/Technology 3	> 100,000
9	Auditing/strategy consulting 3	> 100,000
10	Automotive manufacturer 3	< 100,000
11	Automotive manufacturer 1	< 50,000
12	Strategy consulting 2	< 50,000
13	Strategy consulting 1	< 25,000
14	IT consulting 1	< 5,000
15	IT consulting 2	< 1,000
16	Data platform supplier	< 1,000
17	Data software supplier 1	< 1,000
18	Data software supplier 2	< 1,000
19	Strategy consulting 4	< 1,000
20	IT consulting 3	< 1,000
<b>Table 2. Company Data</b>		

Our experts are therefore experienced domain experts. If the goal is to define suitable data analytics competencies for procurement departments, we believe that in-depth knowledge of data analytics and procurement is necessary on the one hand and extensive experience in working with procurement departments on the other. In this way, the day-to-day problems and requirements of employees in procurement departments can be assessed. We expected at least three years of professional experience. Furthermore, all experts have a focus on the topic of procurement directly or on the broader topic of supply chain, either from previous projects in the case of the experts from consulting companies or due to their organizational responsibilities in the case of the experts from industrial companies. About 74 percent of interviewees have more than seven years of professional experience, and about 35 percent even have more than ten years. The interviewees included both more technically oriented data scientists with different levels of experience as well as project directors and managers from lower, middle, and high management levels. Regarding the companies of our interviewees, our sample consists of 20 different ones. 45 percent of these companies have more than 100,000 employees. 25 percent of the companies have between 1,000 and 100,000 employees. Correspondingly, 30 percent of the companies of our interviewees have less than 1,000 employees. Thus, we cover quite a wide range and include expert knowledge from different company perspectives in our results. We conducted our interviews between July and December 2021. First, we created an interview script and sent it to the interview partners. In total, we sent 30 requests to desired interview partners of which the already mentioned 23 interviewees agreed. The guide contained several questions in the following content clusters:

- Questions about the person, role, and tasks in the organization
- Questions about relevant data in procurement departments
- Questions about data availability and data quality in procurement departments
- Questions about optimizations of data availability and data quality in procurement departments
- Questions about relevant data competencies in procurement departments

The 30 requested expert contacts resulted from previous or ongoing projects, and we aimed to recruit as many of these experts as possible for our interviews to use the widest possible range of experience. Table 3 summarizes the interviewee data, including their job descriptions, their experience, their company related to Table 2, and further interview data regarding interview durations and dates as well as the format in which the interviews were conducted.

Position Interviewee	Experience in Years	Company ID	Duration	Interview Date
Head of Data Platforms & Solutions	> 15	14	29:24	07/14/2021*
Senior Data Analyst Controlling	> 10	11	31:21	07/16/2021*
Data Application Manager	> 7	11	30:41	07/23/2021*
Senior Data Management Architect	> 5	11	35:03	08/03/2021**
Senior Expert Data Analytics	> 7	1	28:57	08/13/2021**
Head of Data Analytics Procurement	> 7	1	39:24	08/19/2021**
Senior Project Manager Analytics	> 5	10	44:14	08/30/2021**
Senior Manager Data Strategy	> 7	13	45:12	09/10/2021*
Manager Business Intelligence	> 10	15	32:35	09/22/2021*
Partner Data Analytics	> 7	12	34:09	09/23/2021**
Senior Data Analyst Procurement	> 10	2	32:04	09/30/2021**
Project Manager Data Analytics	> 10	3	30:32	10/07/2021**
Manager Data Strategy	> 5	4	37:02	10/13/2021**
Team Lead Data Strategy	> 3	16	28:33	10/27/2021**
Key Account	> 7	17	28:44	10/28/2021**
Senior Manager Analytics	> 7	5	38:56	11/03/2021**
Lead Developer Automotive	> 5	18	29:11	11/09/2021**
Manager Analytics	> 5	19	35:04	11/16/2021**
Senior Manager Business Intelligence	> 7	6	29:38	11/17/2021**
Senior Data Scientist	> 7	7	34:55	11/19/2021**
Manager Data Strategy Automotive	> 15	20	36:14	11/26/2021**
Lead Data Scientist	> 10	8	27:55	12/03/2021**
Associate Partner Business Intelligence	> 10	9	36:17	12/10/2021**
* Interview was conducted on site ** Interview was conducted online				
<b>Table 3. Interviewee Data</b>				

The script was based on findings from current research and included the objectives of our planned research, which were scaffolded by the domain-general data analytics from Ghasemaghaei et al. (2018) (see Figure 1). The questions were also based on current research findings that were analyzed in the preliminary work, as discussed in the explanation of the theoretical background. Current challenges and crises were specifically addressed during the interviews. Many contacts with the interviewees arose from previous projects. As a result, past and current crises in particular were very present. However, general and ongoing challenges in the automotive industry were also deliberately addressed. All questions were open-ended, so that there was always the possibility for further questions, additional topics, or linked discussions. During the interviews, all questions were asked in the same order. In some cases, further conversations ensued, and the order of the questions was resumed afterwards.

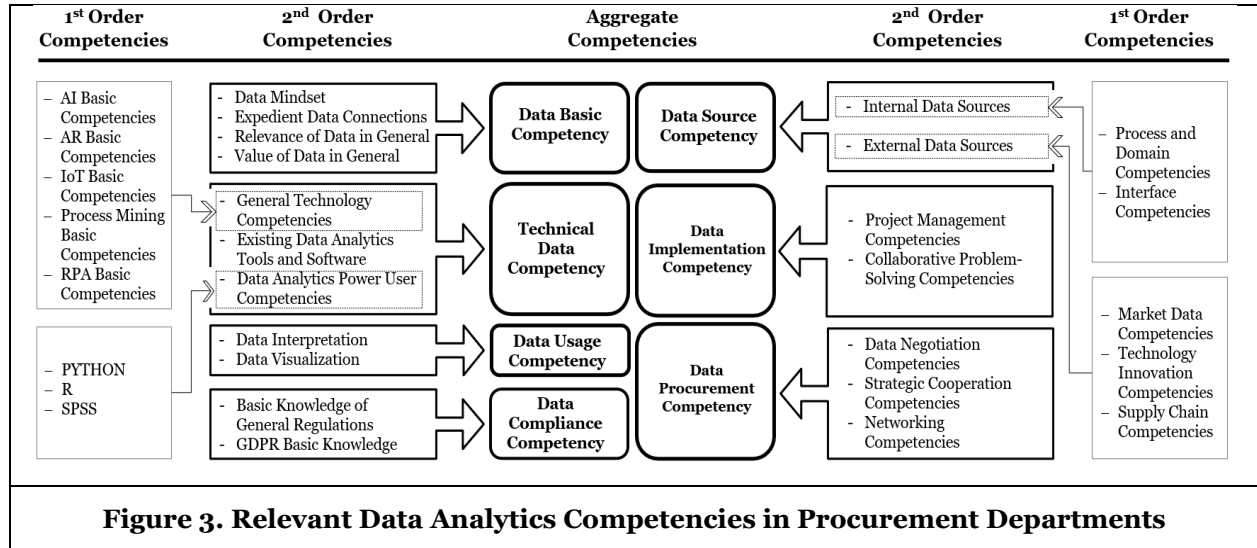
The questions were created based on the findings for successfully managing interviews and creating rich results according to Schultze and Avital (2011). Finally, we asked one more open question for further approaches or aspects to take this goal into account. At this point, the interviewees could report without restrictions on their experiences and ideas. For the purposes of this paper, the topic of data analytics competencies is particularly relevant. The other interview results will be analyzed in greater depth in subsequent research projects. Seven interviews were conducted on site, and the remaining ones were conducted in digital form via video interviews with appropriate software. All interviews were conducted in German. We recorded them with the consent of the interviewees and transcribed them afterwards to ensure that all important information could be evaluated. Building on this, we collected all competencies mentioned by the experts. Based on commonalities and connections, we categorized them according to Gioia et al. (2013). In this way, we obtained a concept-centric and structured overview of the qualitative interview results. The final results will be explained in detail in the following discussion section.



## Findings and Discussion

### Research Findings

As explained in the methodology section, we were able to benefit from heterogeneous expert knowledge within the interviews. Figure 3 presents the results of the interviews and includes all extracted data analytics competencies named by experts after open coding and categorizing the results as described within the methodology section.



While the experts from the automotive manufacturers were mainly able to report on direct experience in their organizations, experts from various consulting companies were able to benefit from numerous projects in the procurement and data environment. Further experts with a focus on procurement and data from IT companies, software and data service providers, and supplier companies also contributed completely new perspectives on relevant data competencies to the interviews. Overall, we obtained a broad overview of necessary data analytics competencies based on experiences from past or currently ongoing projects, initiatives, or transformations. For a better overview, we summarized the results and formed clusters.

First, the experts mentioned competencies such as a general understanding of data or data mindset, recognizing and using meaningful data links, and identifying the general relevance and value of data. We summarized these competencies as “Data Basic Competency”. An adequate data mindset sounds almost self-evident, but this must be developed and implemented in practice. Making decisions based on data rather than instinct, especially when the data leads to different results than intuition would have suggested, are values that first have to develop in everyday practice (Mikalef et al. 2019). Other competencies, such as recognizing useful data connections in order to generate new insights, are also an important component and a basis for the use of data. Thus, a deep understanding of complex data relationships is a basic requirement but must also be developed first (Persaud 2020).

*“The focus on our case, and I see this as the most important asset in people’s minds or rather in people’s competencies, is on whether they have information-linking competencies”* (Interview ID14, Team Lead Data Strategy, Data Platform Supplier).

In the automotive procurement context, experts mentioned such competencies several times by emphasizing different data types from supply chains, where it is important that data is linked in a meaningful way to generate important insights. Such data basic competencies are relevant for operational buyers and not only for dedicated analytics teams, especially in crisis situations, because buyers have a direct line to suppliers, as the experts highlighted.

Our next cluster focuses on dealing with data laws, requirements, and regulations. The supposedly most discussed topic in this context is the General Data Protection Regulation (GDPR) of the European Union. However, the topic of data protection is omnipresent regardless of the GDPR and is described as a necessary competency in numerous research findings (Mikalef and Krogstie 2019).

*“What data protection classifications certain data should have, to what extent secrecy must also be observed here, and what guidelines are attached to it. Buyers need to know this about their data. Then projects can run smoothly, and you can do something valuable with data”* (Interview ID10, Partner Data Analytics, Strategy Consulting 2).

Several experts told us about the need for competencies in the areas of data privacy, data security, or related fields because many specifications are also regulated on a company-specific basis in order to comply with legal requirements. If this competency was not present in projects, massive delays and problems occurred and led to limited results. This was never about pronounced expert competency but rather about necessary basic knowledge. In the procurement context, buyers deal with contracts and related data protection on a daily basis. When exchanging data with suppliers, for example, such competencies are necessary, as the experts pointed out.

Furthermore, several experts mentioned technical competencies, which is not surprising at first. Many of the competencies are based on new technology that has been brought into use in procurement departments or is currently being implemented. Examples from the interview are augmented reality (AR) for virtual walk-throughs or technical collaboration in different locations, the internet of things (IoT) for extracting, among others, sensor data, robotic process automation (RPA) for designing processes with less manual work or artificial intelligence (AI) for smart insights in reports or the prediction of demand quantities. In this context, collaborating with AI startups to obtain dedicated information will become an important aspect of buyers' daily work in the future, which also requires a basic AI competency to be able to ensure the quality of the data for procurement purposes, according to the interviewed experts. An AI startup can be described as a digital startup having AI as a core component of its business model (Schulte-Althoff et al. 2021). Some experts emphasized a necessary curiosity for new technologies. It is not necessary for buyers to be technical developers. However, there should be a basic understanding of the technologies, including an understanding of responsible stakeholders knowing how these technologies work. This promotes efficient implementation in the organization.

*“New applications, new tools, new apps, disruptive technologies like big data, AI, and predictive applications. Many changes are necessary, and buyers need to be able to incorporate them perfectly into their daily lives as needed and realize their full potential”* (Interview ID16, Senior Manager Analytics, Strategy Consulting 3).

In this context, curiosity can also be seen as a competency that is highly relevant for dealing with data-relevant topics (Mikalef and Krogstie 2019). Several times, experts stated the need for knowledge by using existing tools and software, which is often not the case. Organizations have already taken numerous steps to extract value from data and use it for decision-making. Due to a lack of competency in handling it, much potential remains unused. Thus, tools and software sophistication have an essential influence on decision-making performance (Ghasemaghahi et al. 2018). In this context, some experts also mentioned other technical competencies, such as Python, R, and SPSS, which we clustered as power user competencies in Table 4 in order to emphasize in this way that not all experts consider such advanced competencies as necessary for buyers. In the operational business of procurement departments, such advanced competencies probably also depend on whether there are dedicated analytics experts or data scientists, or whether buyers independently implement advanced data analytics for decision-making.

Our next cluster contains capabilities that deal directly with data sources. First, internal sources include processes and domains of buyers as well as related internal expertise. Building on this, process and domain expertise have a significant influence on decision-making performance (Ghasemaghahi et al. 2018). Experts also often mentioned an interface competency and mostly distinguished this from domain knowledge. This goes hand in hand with the role of procurement mentioned in the introduction, which represents a central link, particularly with regard to the supply chain (Pellengahr et al. 2016).

*“On the one hand, procurement is the entrance for suppliers and thus the door to external stakeholders. Inwardly, it needs data from the research and development department, data from the finance department, data from the sales department, the logistics department, and the production department”* (Interview ID9, Manager Business Intelligence, IT Consulting 2).

Building on this, the external sources refer to relevant market data, technological innovations, and the supply chain context. The experts emphasized the role of procurement departments in having the initial position in the value chain and thus must pay attention to important topics, such as the screening of innovations or competitive data, because this data can also have a decisive influence on sourcing decisions or even on the entire alignment of the strategy. In this way, procurement departments can also take on a much more strategic part in the overall organization and further realign its role (Pellengahr et al. 2016).

*“Many innovations in the next few years will come from suppliers or competitors or startups”* (Interview ID23, Associate Partner Business Intelligence, Auditing/strategy consulting 3)

With our next cluster “Data Usage Competency”, we summarize competencies with a focus on using and visualizing data. The experts emphasized several times that competency of interpreting data appropriately is of high relevance but is often not sufficiently available in organizations. Connecting the business problems or other issues with data by interpreting data correctly and then using it for decision-making is an important competency with high value for handling data (Mikalef and Krogstie 2019). Connected with this, experts noted data visualization competency to present data results in suitable ways for different recipients, because buyers have to make decisions in various committees on an almost daily basis, for example for supplier sourcing decisions or budgets. Furthermore, experts emphasized the data-driven processes, especially in crisis situations, so that such competencies were named as highly relevant for buyers by several experts.

*“And then we also do qualifications in data visualization. I think that's also an important competency. How can I present it for my desired recipients? It is important to be able to assess the degree of aggregation because it differs massively depending on the recipients. Especially in procurement, there are so many committees with different management levels”* (Interview ID16, Senior Manager Analytics, Strategy consulting 3).

With our cluster “Data Implementation Competency”, we summarized competencies that experts marked as relevant for data analytics activities in daily procurement processes. First, experts mentioned project management skills several times as very important in procurement departments. In most cases, they cited the project character of activities for creating new reports or reporting applications as the reason for this. Based on this, preceding activities such as data source connections, data preparation or data linking must also be handled in projects of varying complexity. In this context, buyers are project managers who must provide input, know data sources and key stakeholders or, lastly, verify that data results are valid. Mikalef and Krogstie (2019) also stated that project management competency has a high relevance for a successful handling of data. Strong project management competencies are also required in many job advertisements by employers when it comes to jobs in data science or related fields (Debortoli et al. 2014; Persaud 2020). According to the experts, this competency is not sufficiently developed in procurement departments but is urgently needed to effectively drive data analytics activities forward.

*“Buyers should be transferred more out of the operational and into the project business. Because many topics take place in projects. [...] Here, we have great pain in projects with customers. [...] Especially the creation of new reports or new key performance indicators are all worked out in projects. [...] Many buyers have never worked in real projects before.”* (Interview ID23, Associate Partner Business Intelligence, Auditing/Strategy Consulting 3)

In a final cluster “Data Procurement Competency”, we summarized very procurement-specific competencies by addressing the negotiation of relevant data. In accordance with the orientation and responsibility of procurement departments as a central interface for internal and external stakeholders mentioned at the beginning, it becomes clear that much relevant data from a buyer’s perspective are located outside one’s own organization and must be procured for further data analytics activities. Here, for example, they are dealing with data that is not simply freely available, but may be held by suppliers or other stakeholders within the supply chain. But even in the case of data that would in principle be freely available, it is necessary to look at how it can be procured and made usable. In the context of data source competency,

we already discussed market, technical innovation, or supply chain data as high-priority data examples for procurement departments.

*“Just as buyers bought services or components in the past and always knew what good quality and prices were, buyers need to know the same for data of all kinds. In the future, these will be things that have to be procured. Data is certainly not procured in the same way as services or components, but it must be brought into the company.”* (Interview ID20, Senior Data Scientist, Engineering/Technology 2)

The first step is knowing relevant data, but the more complex step is making these data sets available in the organization. Whereas market data or technical innovation data is often available, it is difficult to access supplier-specific data. Experts mentioned sub-supplier structures or technical specifics of components as examples. The data output must be negotiated by buyers, either contractually at the beginning of procurement processes or afterwards. This requires competency because the subject of negotiation in the form of data has not previously been part of the activities of buyers, which immediately leads to the next procurement-specific competency that experts mentioned.

*“Often, data is located outside the organization. To access this data, contracts are usually required, which is not always easy. Therefore, competency is needed to ensure strategic exchange. [...] These are completely new competencies for buyers.”* (Interview ID8, Senior Manager Data Strategy, Strategy Consulting 1)

In the interviews, experts described a strategic cooperation competency. The focus was primarily on the supply chain. According to the experts, this kind of competency is based on the fact that it is often more expedient to develop strategic cooperation agreements with relevant suppliers and thus permanently increase transparency in the supply chain by exchanging relevant data. The last competency mentioned in the interviews, which we called networking competency, also fits into this context.

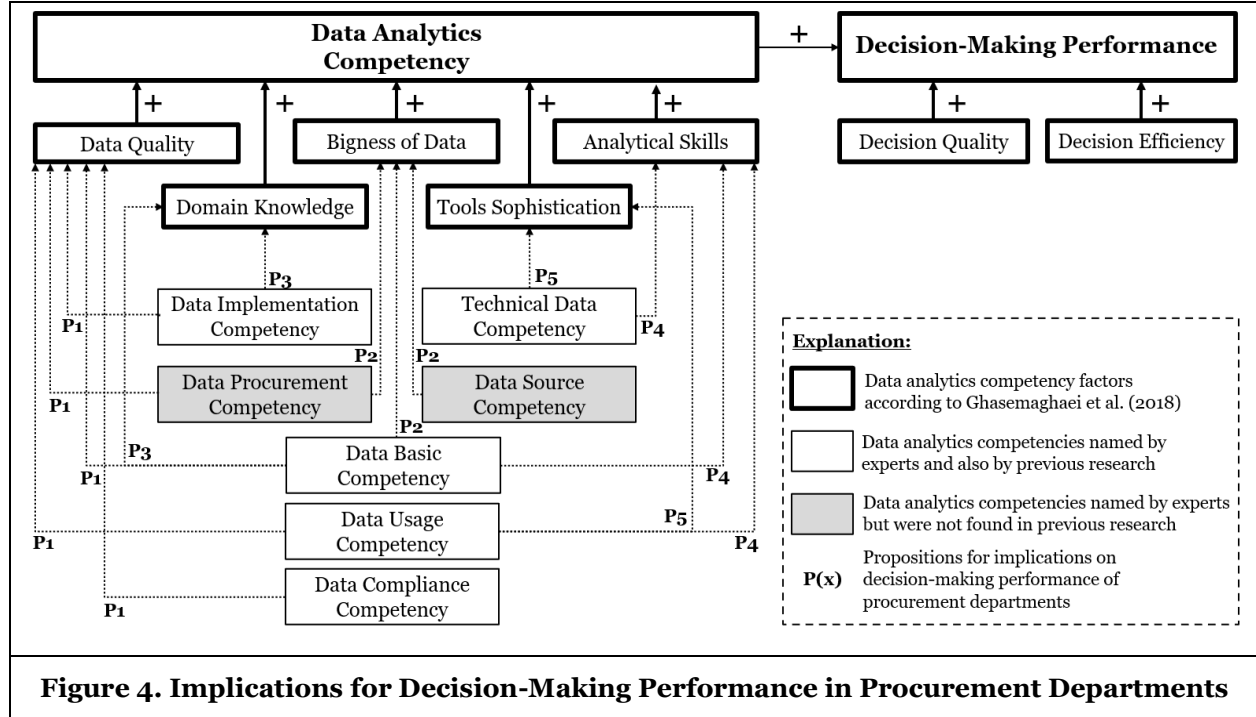
*“When data is important but no longer resides within your own organization, buyers must have networking skills. Networking with other automotive manufacturers, with suppliers, with tech companies, and with universities.”* (Interview ID17, Lead Developer Automotive, Data Software Supplier 2)

In the context of these competencies, the automotive network Catena-X was also mentioned in which a secure and standardized data exchange between all members is stated as the primary objective. At this point, it becomes clear that buyers are performing activities that were not part of their job content before. In the next section we build on our extracted data analytics competencies to derive implications for decision-making performance.

### ***Deriving Implications for Decision-Making***

First, we found that many of the data analytics competencies identified in previous research are also relevant in procurement departments. Figure 4 illustrates our results and also presents our propositions regarding the implications for decision-making in procurement departments, which we derive in detail below. We already identified the first differences within further specifications of these competencies. In addition, the experts named further competencies that we were unable to identify within the analyzed research approaches. Thus, all of the specific data analytics competencies that we had categorized in the clusters of “Data Compliance Competency”, “Data Usage Competency”, “Data Basic Competency”, and “Data Implementation Competency” were also found in previous research results. There were, however, also significant differences in the degree of technical data competencies. Whereas previous research results defined very pronounced competencies, including programming or database knowledge (Mikalef and Krogstie 2019), the experts' statements referred more to a basic competency for new technologies or pronounced competency for existing tools and software as necessary competencies for buyers. At this point, it becomes clear that buyers should not be data scientists, nor do they have to be. Rather, they need to have a basic technical understanding of relevant software or systems in their field of work in order to support and promote their actual tasks with data-relevant activities. Although the experts mentioned competencies in the use of Python, R, or SPSS, this was primarily in the context of so-called power user competencies,

which not all buyers require. Competencies that we categorized in the “Data Procurement Competency” and “Data Source Competency” clusters could not be found in previous research. Both clusters are probably relevant also due to the scope and responsibilities of procurement departments. We had already explained that much relevant data for procurement departments lie in organizational areas outside of procurement or also outside of the organization. Thus, the management of internal and external data sources seems to be an important competency for buyers in the context of data analytics.



The experts also emphasized the need of procuring relevant data, such as components, as these are often held by supply chain partners and are not freely available. In this context, the experts also referred to distinctive network competencies, which, according to the experts, can lead to much added value for procurement departments if cooperation and data exchange agree in this way. At this point, it can be stated that the extracted procurement-specific data analytics competencies are not necessarily relevant exclusively in procurement departments but also in other organizational areas. We focus on a procurement perspective in relation to previous general research. On the one hand, the differences to previous research results are highlighted, and, on the other hand, our data analytics competencies are related to the approach of (Ghasemaghaei et al. 2018). For deriving implications of our analyzed data analytics competencies for decision-making in procurement departments, we analyzed the five competency dimensions according to (Ghasemaghaei et al. 2018) and mapped our competencies. In this way, we can derive value propositions on how the analyzed procurement-specific data analytics competencies can influence decision-making.

These relationships are also illustrated in Figure 4. First, we see several connections between our data analytics competency clusters and the data quality dimension. As already discussed, data quality is defined by using four categories: intrinsic, contextual, representational, and accessibility (Wang and Strong 1996). If many data analytics activities are carried out in a project format, as many experts emphasize, we can state that competencies of our data implementation cluster, like project management or problem-solving competency, influence data quality. Hence, data quality is defined, developed and measured in projects. Furthermore, we see effects of data procurement competency on data quality. As explained earlier, experts see a need for sourcing data such as components or services. Data quality also includes the relevance and the availability of data (Ghasemaghaei et al. 2018). For procuring data, it can be assumed that the focus is on access to relevant data, which clearly means that data quality is taken into account at this point. In this context, it can be stated that data basic competency also has implications for data quality, as experts have mentioned competencies such as being able to recognize the value of data or purposeful connections

between data. Data usage competency includes competencies such as interpreting and visualizing data, which is a direct link to the representational category of data quality (Ghasemaghaei et al. 2018). Lastly, we see implications of data compliance competency on data quality, since data quality ends where laws or other regulations set the limits in handling data, as the experts made clear to us. Based on these content matches, we propose the following implications of our extracted specific data analytics competencies for data quality:

1. Data implementation, data procurement, data basic, data usage, and data compliance competency have implications for data quality and, thus, for data analytics competency and decision-making in procurement departments.

Building on this, bigness of data as a dimension describes an ever-increasing amount of new data (Lycett 2013). We see implications of data procurement, data source, and data basic competency for the dimension bigness of data according to Ghasemaghaei et al. (2018). As explained above, these competencies are about recognizing relevant data and their connections, identifying and managing relevant internal and external data sources and procuring these data sets for analyzing it within the organization. Bigness of data as one of the most critical strategic resources is essential to generate value from data to support decision-making (Fernández et al. 2014). If relevant data for procurement departments must be procured according to the experts' statements of relevant competencies for buyers, we propose implications for the bigness of data. Therefore, we derive the following proposition:

2. Data procurement, data basic, and data source competency have implications for the bigness of data and, thus, for data analytics competency and decision-making in procurement departments.

Furthermore, we see implications of data implementation and data basic competency for the domain knowledge dimension according to Ghasemaghaei et al. (2018). Strong domain knowledge can help to better solve key attributes and business problems and, thus, enables successful data analytics (Sukumar and Ferrell 2013). Data implementation competency as a cluster for project management and problem-solving competency has implications for this dimension from our perspective. Hence, several data analytics activities are conducted in projects, which also includes business problems and valuable problem-solving. As a result, we propose the following:

3. Data implementation and data basic competency have implications for domain knowledge and, thus, for data analytics competency and decision-making in procurement departments.

Using data analytics for improving decision-making in organizations characterizes analytical skills as a further dimension (Wong 2012). We see implications of technical data, data basic, and data usage competency for this dimension. Technical data competency includes, among others, basic competencies in dealing with existing software and tools within the organization but also with new technologies, according to experts. A professional use of technologies of all kinds is a basic requirement for the management of data (van de Wetering et al. 2019). Furthermore, the recognition and connection of valuable data and subsequent activities such as target-oriented interpretation and visualization were highlighted by experts as relevant competencies in procurement departments. Therefore, we propose implications of these competencies for the analytical skills dimension, as they reflect the content of this dimension according to Ghasemaghaei et al. (2018):

4. Technical data, data basic and data usage competency have implications for analytical skill and, thus, for data analytics competency and decision-making in procurement departments.

Finally, tools sophistication as a dimension describes both the complexity and maturity of the systems (Chwelos et al. 2001) and the functional scope for generating new insights to improve decision-making (Gillon et al. 2014). We propose implications of technical data and data usage competency for this dimension. As already discussed, technical data competency summarizes the handling of existing software and tools as well as new technologies that were mentioned by experts as relevant competencies for buyers. In our perspective, this is a direct link to the maturity of the systems and presumably also has an influence on their complexity or the manageability of this complexity. In this context, the preparation and use of data, which we have summarized in our data usage competency cluster, probably also have implications because these activities are carried out with the help of existing systems.

5. Technical data and data usage competency have implications for tools sophistication and, thus, for data analytics competency and decision-making in procurement departments.

Further implications are certainly possible. At this point, we used content mapping as a method to demonstrate that our extracted data analytics competencies can also have implications for decision-making in procurement departments. We included what we considered to be the key aspects of content but do not claim to provide a final and conclusive analysis.

### ***Theoretical and Practical Contributions***

Our research findings have both theoretical and practical implications. Our research contributes a procurement perspective to previous findings. Research has identified numerous important data analytics competencies by using several approaches. In summary, it can be stated that there is pronounced knowledge of relevant data analytics competencies in research. With our focus on procurement-specific competency requirements, we directed the focus on a sub-area in organizations and talked to experienced experts about detailed demands in procurement departments, which has not yet been analyzed in previous research. The procurement perspective is exciting because massive cost damage has been caused to companies, especially by supply disruptions in recent years. On average, companies lost 182 million US dollars due to supply disruption (Interos Report 2022). Among others, 750 procurement leaders were surveyed for their organizations. If data analytics competencies can contribute to improving decision-making in procurement departments, then this is a valuable subject for investigation. Through our findings, we were able to show, independently of the organizational area of procurement, that it can be promising to analyze data analytics competencies specifically in sub-areas as a further theoretical contribution. In this way, we were able to show that there are several data analytics competencies from previous research findings that are relevant to procurement departments as well., but there can also be significant differences in specific organizational areas. Such an analysis in other departments of organizations may possibly lead to further specific findings. Therefore, intensifying research in specific business areas can lead to valuable insights. Specifying research can also improve the link to practice, as decision makers rely on adapted research in their areas of responsibility for translating research findings into practical activities.

Building on this, our research includes, above all, practical contributions, which we would like to emphasize. We were able to show that in procurement departments, in addition to the well-known data analytics competencies, there are further very specific ones that can lead to valuable improvements in decision-making, according to experienced procurement experts. It became clear during the interviews that buyers are faced with the challenge that relevant data often lie outside their own organizations and that data source competency is required to identify relevant data sets. In the interviews, the experts also highlighted the need for a data procurement competency because this relevant data is usually not freely available but is held by suppliers or other business partners and therefore has to be negotiated, such as component parts or services. In addition, we were able to show that not all data analytics competencies known to date are equally relevant for buyers. For example, the experts see technical data competencies only at a certain level in procurement departments. In addition to the theoretical development of research in the field of data analytics competencies as described above, we want to use our results to support procurement leaders and their departments in obtaining a structured overview of helpful competencies in dealing with data in order to improve decision-making in their organizations. As described above, crises are a challenge for organizations worldwide. One example is the competency to establish data-based transparency of internal and external stakeholders of supply chains, which come into focus especially in crises (Pellengahr et al. 2016). Procurement departments as the responsible entities for the supply chain are often the focus in crisis situations (Ahuja and Ngai 2019). Effective decision-making is essential in this context, and data analytics can be a key activity in overcoming these challenges (Chae et al. 2014; Chen et al. 2012). However, this also requires the right competencies among responsible buyers (Liberatore and Luo 2013; Persaud 2020; Shuradze and Wagner 2016). Therefore, we see practical implications based on our findings to support organizations in this identification of necessary data analytics competencies.

## **Conclusion**

Our overarching research question was to figure out relevant and generalizable data analytics competencies for employees in procurement departments and resulting implications on decision-making. For this purpose, we conducted expert interviews and linked the results to existing approaches from previous research. Based on this previous research in the field of data analytics competencies combined with the experience of the interviewed experts, we were able to show that certain data analytics competencies, which have been evaluated so far, are also relevant for procurement departments in this way. However, there are also specific competencies that, according to the experience of experts, are highly relevant for procurement departments for the overriding goal of effective decision-making but have not been part of research findings so far. In this context, experts named data source and data procurement competencies that arise from the fact that relevant data for procurement often lie outside the company's own boundaries and therefore need to be identified and made usable. Based on the research of Ghasemaghaei et al. (2018), we also propose detailed implications of these competencies for decision-making in procurement departments. With our results, we want to contribute to the current research in the field of data analytics competencies by adding a specific procurement perspective. We also want to contribute to the situation of procurement departments in the environment of crises and necessary effective decision-making. In this context, we have already emphasized that data analytics is only one of certainly many possible activities for facing crises and uncertainty, but it is a promising one, since many decisions can be made more efficiently on the basis of data in order to counteract challenges of all kinds (Chae et al. 2014; Chen et al. 2012; Olszak and Zurada 2019).

However, our research also has limitations. First of all, it must be emphasized that data analytics competency is a fast-moving topic and research findings represent a snapshot. Continuous research is required in order to pay attention to technical, economic or other developments and changes. We were only able to use a subset for analysis due to the volume of existing research. Meanwhile, research in this area continues to progress. More key data analytics competencies are likely to be available in further research approaches. Furthermore, organizations must also observe constant change and constantly reassess the necessary competencies in the field of data analytics. In our research, we pursued the goal of extracting input from the broadest possible base of expertise. Therefore, we conducted our interviews on a broad range of expert knowledge by including different industries, experience levels, and positions or diverse perspectives, but all of them with regard to procurement and data analytics. Nevertheless, the results do not yet reflect all conceivable perspectives. Further experts are likely to have different experiences, supplementary relevant information, or possibly even divergent opinions on relevant data analytics competencies. We cannot completely rule out all biases induced through the recruitment of interview partners. Furthermore, we extracted our results based on experiences in the automotive industry. Direct applicability to procurement departments in other industries requires further investigation. We do not claim for our research to be complete or to have the only correct view of relevant competencies in procurement departments. Building on this, other perspectives of analysis can lead to further valuable findings. For example, an extended analysis of end users and their perspectives of existing deficits, or also further best practices in the use of data for decision-making, can provide complementary insights that complete the big picture of relevant data analytics competencies in procurement departments. Finally, it is important to emphasize that the implications of the analyzed data analytics competencies for decision-making in procurement departments are based on propositions and were elaborated by using content mappings to the existing approach by Ghasemaghaei et al. (2018). The authors quantitatively measured the impact of the five dimensions of data analytics competency and the impact on decision-making performance in their approach. Finally, a more in-depth measurement of our mappings to these dimensions may provide more detailed insights.

Based on our overarching research question, we primarily emphasized the practical contribution of our research. However, our findings are based on relevant previous research and with our addition of a procurement perspective, we were able to demonstrate that it can be valuable to investigate data analytics competencies in specific organizational departments. In our next research steps, we will build on the previous findings and investigate further facets of data analytics competencies. In doing so, we will also pay further attention to our five developed propositions.



## References

- Ahuja, T. S. A., and Ngai, Y. 2019. "Shifting the Dial in Procurement," available at <https://www.mckinsey.com/business-functions/operations/our-insights/shifting-the-dial-in-procurement>.
- Bharadwaj, A. S. 2000. "A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation," *MIS Quarterly* (24:1), p. 169 (doi: 10.2307/3250983).
- Burnard, K., Bhamra, R., and Tsinopoulos, C. 2018. "Building Organizational Resilience: Four Configurations," *IEEE Transactions on Engineering Management* (65:3), pp. 351-362 (doi: 10.1109/tem.2018.2796181).
- Chae, B., Yang, C., Olson, D., and Sheu, C. 2014. "The impact of advanced analytics and data accuracy on operational performance: A contingent resource based theory (RBT) perspective," *Decision Support Systems* (59), pp. 119-126 (doi: 10.1016/j.dss.2013.10.012).
- Chen, H., Chiang, R. H. L., and Storey, V. C. 2012. "Business Intelligence and Analytics: From Big Data to Big Impact," *MIS Quarterly* (36:4), pp. 1165-1188.
- Chwelos, P., Benbasat, I., and Dexter, A. S. 2001. "Research Report: Empirical Test of an EDI Adoption Model," *Information Systems Research* (12:3), pp. 304-321 (doi: 10.1287/isre.12.3.304.9708).
- Debortoli, S., Müller, O., and Vom Brocke, J. 2014. "Comparing Business Intelligence and Big Data Skills," *Business & Information Systems Engineering* (6:5), pp. 289-300 (doi: 10.1007/s12599-014-0344-2).
- Dhurandhar, A., Graves, B., Ravi, R., Maniachari, G., and Ettl, M. 2015. "Big Data System for Analyzing Risky Procurement Entities," *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '15*, pp. 1741-1750 (doi: 10.1145/2783258.2788563).
- Farrokhi, A., Shirazi, F., Hajli, N., and Tajvidi, M. 2020. "Using artificial intelligence to detect crisis related to events: Decision making in B2B by artificial intelligence," *Industrial Marketing Management* (91), pp. 257-273 (doi: 10.1016/j.indmarman.2020.09.015).
- Fernández, A., Del Río, S., López, V., Bawakid, A., Del Jesus, M. J., Benítez, J. M., and Herrera, F. 2014. "Big Data with Cloud Computing: an insight on the computing environment, MapReduce, and programming frameworks," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* (4:5), pp. 380-409 (doi: 10.1002/widm.1134).
- Gao, P., Müller, N., Kaas, H.-W., Mohr, D., Wee, D., Hensley, R., Guan, M., Möller, T., Eckhard, G., Bray, G., Beiker, S., Brotschi, A., and Kohler, D. 2016. "Automotive Revolution Perspective Towards 2030," *McKinsey Report*.
- Ghasemaghaei, M., Ebrahimi, S., and Hassanein, K. 2018. "Data analytics competency for improving firm decision making performance," *The Journal of Strategic Information Systems* (27:1), pp. 101-113 (doi: 10.1016/j.jsis.2017.10.001).
- Gillon, K., Aral, S., Lin, C.-Y., Mithas, S., and Zozulia, M. 2014. "Business Analytics: Radical Shift or Incremental Change?" *Communications of the Association for Information Systems* (34) (doi: 10.17705/1CAIS.03413).
- Gioia, D. A., Corley, K. G., and Hamilton, A. L. 2013. "Seeking Qualitative Rigor in Inductive Research," *Organizational Research Methods* (16:1), pp. 15-31 (doi: 10.1177/1094428112452151).
- Gorman, M. F., and Klimberg, R. K. 2014. "Benchmarking Academic Programs in Business Analytics," *Interfaces* (44:3), pp. 329-341 (doi: 10.1287/inte.2014.0739).
- Hanelt, A., Piccinini, E., Gregory, R. W., Hildebrandt, B., and Kolbe, L. M. 2015. "Digital Transformation of Primarily Physical Industries-Exploring the Impact of Digital Trends on Business Models of Automobile Manufacturers," *12. Internationalen Tagung Wirtschaftsinformatik*.
- Holling, C. S. 1996. "Engineering Resilience Versus Ecological Resilience," *Engineering within Ecological Constraints*, pp. 31-43.
- Interos Report. 2022. "Resilience 2022 - The Interos Annual Global Supply Chain Report," available at [https://www.interos.ai/wp-content/uploads/2022/05/Resilience-2022\\_Interos\\_Annual-Global-Supply-Chain-Report\\_5\\_11\\_2022.pdf](https://www.interos.ai/wp-content/uploads/2022/05/Resilience-2022_Interos_Annual-Global-Supply-Chain-Report_5_11_2022.pdf), accessed on Aug 17 2022.
- Klee, S., Janson, A., and Leimeister, J. M. 2021. "How Data Analytics Competencies Can Foster Business Value— A Systematic Review and Way Forward," *Information Systems Management* (38:3), pp. 200-217 (doi: 10.1080/10580530.2021.1894515).
- Kurz, R., and Bartram, D. 2008. "Competency and Individual Performance: Modelling the World of Work," *The Journal of applied psychology*, pp. 227-255 (doi: 10.1002/9780470696736.ch10).

- Liberatore, M., and Luo, W. 2013. "ASP, The Art and Science of Practice: A Comparison of Technical and Soft Skill Requirements for Analytics and OR Professionals," *Interfaces* (43:2), pp. 194-197 (doi: 10.1287/inte.1120.0647).
- Lycett, M. 2013. "'Datafication': making sense of (big) data in a complex world," *European Journal of Information Systems* (22:4), pp. 381-386 (doi: 10.1057/ejis.2013.10).
- Mauro, A. d., Greco, M., Grimaldi, M., and Ritala, P. 2018. "Human resources for Big Data professions: A systematic classification of job roles and required skill sets," *Information Processing & Management* (54:5), pp. 807-817 (doi: 10.1016/j.ipm.2017.05.004).
- Mikalef, P., Boura, M., Lekakos, G., and Krogstie, J. 2019. "Big data analytics and firm performance: Findings from a mixed-method approach," *Journal of Business Research* (98), pp. 261-276 (doi: 10.1016/j.jbusres.2019.01.044).
- Mikalef, P., and Krogstie, J. 2019. "Investigating the Data Science Skill Gap: An Empirical Analysis," *Proceedings of 2019 IEEE Global Engineering Education Conference (EDUCON)*, pp. 1275-1284.
- Olszak, C. M., and Zurada, J. 2019. "Big Data in Capturing Business Value," *Information Systems Management* (37:3), pp. 240-254 (doi: 10.1080/10580530.2020.1696551).
- Pellengahr, K., Schulte, A. T., Richard, J., and Berg, M. 2016. "Einkauf 4.0 – Digitalisierung des Einkaufs," *Vorstudie des Fraunhofer IML und Bundesverband Materialwirtschaft, Einkauf und Logistik e.V. (BME)*.
- Persaud, A. 2020. "Key competencies for big data analytics professions: a multimethod study," *Information Technology & People* (ahead-of-print:ahead-of-print), p. 113 (doi: 10.1108/ITP-06-2019-0290).
- Qadir, J., Ali, A., ur Rasool, R., Zwitter, A., Sathiaselan, A., and Crowcroft, J. 2016. "Crisis analytics: big data-driven crisis response," *Journal of International Humanitarian Action* (1:1) (doi: 10.1186/s41018-016-0013-9).
- Rialti, R., Zollo, L., Ferraris, A., and Alon, I. 2019. "Big data analytics capabilities and performance: Evidence from a moderated multi-mediation model," *Technological Forecasting and Social Change* (149), p. 119781 (doi: 10.1016/j.techfore.2019.119781).
- Schulte-Althoff, M., Fürstenau, D., and Lee, G. M. 2021. "A Scaling Perspective on AI Startups," *Hawaii International Conference on System Sciences 2021*.
- Schultze, U., and Avital, M. 2011. "Designing interviews to generate rich data for information systems research," *Information and Organization* (21:1), pp. 1-16 (doi: 10.1016/j.infoandorg.2010.11.001).
- Shuradze, G., and Wagner, H.-T. 2016. "Towards a Conceptualization of Data Analytics Capabilities," *2016 49th Hawaii International Conference on System Sciences (HICSS)*, pp. 5052-5064 (doi: 10.1109/HICSS.2016.626).
- Simonji-Elias, M., Collyer, M., Johnston, M., Lichtenfeld, L., Lund, J., and Staiger, J. 2014. "KPMG's Global Automotive Executive Survey 2014," *KPMG Study*.
- Sukumar, S. R., and Ferrell, R. K. 2013. "'Big Data' collaboration: Exploring, recording and sharing enterprise knowledge," *Information Services & Use* (33:3-4), pp. 257-270 (doi: 10.3233/ISU-130712).
- van de Wetering, R., Mikalef, P., and Krogstie, J. 2019. "Strategic Value Creation through Big Data Analytics Capabilities: A Configurational Approach," *2019 IEEE 21st Conference on Business Informatics (CBI)*, pp. 268-275 (doi: 10.1109/CBI.2019.00037).
- Wang, R. Y., and Strong, D. M. 1996. "Beyond Accuracy: What Data Quality Means to Data Consumers," *Journal of Management Information Systems* (12:4), pp. 5-33 (doi: 10.1080/07421222.1996.11518099).
- Wang, S., Yeoh, W., Richards, G., Wong, S. F., and Chang, Y. 2019. "Harnessing business analytics value through organizational absorptive capacity," *Information & Management* (56:7), p. 103152 (doi: 10.1016/j.im.2019.02.007).
- Wang, W., Street, W. N., and deMatta, R. E. 2015. "Topological Resilience Analysis of Supply Networks under Random Disruptions and Targeted Attacks," *Proceedings of the 2015 IEEE/ACM International Conference*, pp. 250-257 (doi: 10.1145/2808797.2809325).
- Wong, D. 2012. "Data is the Next Frontier, Analytics the New Tool: Five trends in big data and analytics, and their implications for innovation and organisations," available at [https://www.biginnovationcentre.com/wp-content/uploads/2019/07/BIC\\_DATA-IS-THE-NEXT-FRONTIER\\_03.11.2012.pdf](https://www.biginnovationcentre.com/wp-content/uploads/2019/07/BIC_DATA-IS-THE-NEXT-FRONTIER_03.11.2012.pdf), accessed on Apr 14 2022.
- Xiang, J. 2014. "Procurement under Incomplete Information about the Supply Disruption," *Conference: 2014 11th International Conference on Service Systems and Service Management (ICSSSM)*.