DEVELOPING DATA ANALYTICS IN PURCHASING AND SUPPLY MANAGEMENT

Case study from service industry

Lappeenranta–Lahti University of Technology LUT

Master of Science in Economics and Business Administration, Master's thesis

Master's programme in Supply Management

2025

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Examiner(s): Professor Jukka Hallikas

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ABSTRACT

Lappeenranta–Lahti University of Technology LUT

LUT Business School

Master's programme in Supply Management

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Developing data analytics in purchasing and supply management: case study from service industry

Master's thesis

2025

71 pages, 7 figures, 5 tables and 1 appendices

Examiner(s): Professor Jukka Hallikas and Associate professor Mika Immonen

Keywords: Supply management, data analytics, service industry

This Master's thesis focuses on understanding how data analytics is utilized in supply management and what kind of development needs are associated with it. The objective of the study is to examine how analytics could be developed in the case company's procurement function. In addition, the study aims to increase the understanding of the benefits of data analytics, the potential barriers to integrating and using analytics, and the reasons why organizations utilize data analytics in their procurement activities.

The thesis was conducted using a qualitative case study method. The research data was collected from the case organization through two interviews. To enhance the reliability of the research findings, secondary data was also used, consisting of publicly available information about the company and materials provided by the interviewees.

The findings indicate that data analytics has become significant part of the procurement decision-making in the case organization. The case company and its procurement function have shifted towards data-driven management, and the use of analytics has brought visible benefits. However, several challenges still limit the full integration of data-based decision-making into the company's processes. The study provides development proposals to address these challenges and further advance the use of data analytics. Based on the results, it can be concluded that the case company is progressing towards a permanent analytics-based operating model.

TIIVISTELMÄ

Lappeenrannan–Lahden teknillinen yliopisto LUT

LUT-kauppakorkeakoulu

Supply Management - Maisteriohjelma

Antti Keinänen

Data-analytiikan kehittäminen hankintatoimessa: case palveluala

Kauppatieteiden pro gradu -tutkielma

2025

71 sivua, 7 kuvaa, 5 taulukkoa ja 1 liitettä

Tarkastaja(t): Professori Jukka Hallikas ja Tutkijaopettaja Mika Immonen

Avainsanat: Hankintatoimi, data-analytiikka, palveluliiketoiminta

Tämä pro gradu -tutkielma keskittyy ymmärtämään, miten data-analytiikkaa hyödynnetään hankintatoimessa ja millaisia kehitystarpeita siihen liittyy. Tutkimuksen tavoitteena on tutkia, miten case-yrityksen tapauksessa analytiikkaa voitaisiin kehittää. Lisäksi tutkimus pyrkii lisäämään ymmärrystä data-analytiikan hyödyistä, minkälaisia esteitä analytiikan integroinnissa ja käyttämisessä voi ilmaantua sekä minkä takia organisaatiot hyödyntävät data-analytiikkaa hankintatoimessaan.

Tutkielma toteutettiin laadullisella tapaustutkimus menetelmällä. Tutkimusaineisto kerättiin kohdeorganisaatiosta kahden haastattelun avulla. Tutkimustulosten luotettavuutta pyrittiin vahvistamaan käyttämällä sekundääriaineistoa, joka koostuu yrityksen julkisista tiedoista sekä haastateltavilta saaduilta aineistoilla.

Tutkimustulokset osoittavat, että data-analytiikka on kehittynyt merkittäväksi osaksi kohdeorganisaation hankintatoimen päätöksentekoa. Case-yritys ja sen hankintaorganisaatio on siirtynyt kohti tiedolla johtamista, ja analytiikan hyödyntäminen on tuonut näkyviä hyötyjä. Analytiikan käyttöä kuitenkin rajoittaa edelleen lukuisat haasteet, jotka ovat hidastuttaneet dataan perustuvan päätöksenteon integroimisen kokonaisvaltaisesti kohdeorganisaation toimintamalleihin. Tutkimuksessa annettiin kehitysehdotuksia, joiden avulla haasteet voidaan ratkaista ja data-analytiikkaa kehittää. Tulosten perusteella voidaan todeta, että kohdeorganisaatio on siirtymässä kohti pysyvää analytiikkapohjaista toimintamallia.

ACKNOWLEDGEMENTS

About five years ago, I arrived in an unknown Lappeenranta, feeling both excited and nervous about what my studies would bring. These five years required a lot of hard work, but at the same time, I learned new things and created countless unforgettable memories. With fascinating studies and close friends by my side, the years passed much faster than I could have ever expected. Now, I am once again standing at a new beginning, feeling the uncertainty of the future, but the memories and lessons from my university years remind me that the future is ultimately bright.

I would like to thank LUT university for providing me with not only a high-quality education but also a valuable degree for my future. I would also like to thank my supervisor Jukka for his guidance and support throughout this project. In addition, I want to express my gratitude to Jari and Mikko from the case organization, whose help made this thesis possible.

I would like to thank my friends and all the fellow students with whom I have completed many of my studies. In particular, I want to thank my close group of friends, with whom I have shared these past five years from the very first day until today. Finally, a special thanks to my family for their support and love throughout these years.

Lappeenranta 19.3.2025

Antti Keinänen

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1 Introduction

Over the past decades, the world has undergone significant changes due to digitalization and globalization. Amid these transformations, numerous companies have increasingly outsourced their operations while focusing solely on their core business functions. This shift has led to the growing importance of purchasing and supply management (PSM) within organizations, prompting researchers and businesses to explore the development opportunities in PSM. With digitalization, technological advancements have accelerated in recent years, driven by innovations such as artificial intelligence and blockchain. Simultaneously, the volume of raw data has exploded as digital systems, such as enterprise resource planning (ERP) systems, have gained the capability to collect vast amounts of data. However, transforming raw data into actionable insights through analytics requires not only advanced systems but also employees with analytical capabilities (Arunachalam, Kumar & Kawalek 2018).

Companies have become increasingly aware of the significance of data, leading to the adoption of data analytics in business operations. This trend is also evident in PSM organizations, as procurement functions can generate critical data for future decision-making. For instance, data collected from spending, supplier performance evaluations, and negotiations can be leveraged for future planning (Wang, Gunasekaran, Ngai & Papadopoulos 2016). In addition to internal data, companies also collect external data to continuously monitor market conditions and enhance resilience. In procurement, external data can be gathered from sources such as social media or news outlets (Wang, Gunasekaran, Ngai & Papadopoulos 2016). Due to globalization, competition among businesses has intensified on an international scale. Companies strive to improve their competitiveness relative to their rivals through data analytics, making its development a key focus for researchers and businesses in recent years.

The utilization and adoption of data analytics in supply chains and supply management have been extensively studied in recent years. Waller and Fawcett (2013) were among the first to investigate the use of big data analytics in supply chains. Since then, the number of scientific publications focusing on data analytics and analytical skills in supply chains has increased significantly (Arunachalam et al. 2018). Researchers have examined, for example, how the development of data analytics could enhance a company's resilience to business risks (Singh & Singh 2019), how analytics can improve companies' performance and supply chain agility (Fosso Wamba & Akter 2019), and how analytics impacts supply chain logistics (Queiroz & Telles 2018). Although the use of data analytics in procurement has been less studied, the interest in this area is growing (Handfield, Jeong & Choi 2019). Öhman, Arvidsson, Jonsson, and Kaipia (2021) examined how analytical skills could be developed in purchasing and supply management. Although data analytics in procurement is an emerging topic, many researchers have addressed the digitalization of procurement in their studies. Procurement digitalization has been examined, for instance, on the role of data analytics (Hallikas, Immonen & Brax 2021), the impact of digitalization on supply chain resilience (Harju, Hallikas, Immonen & Lintukangas 2023), and procurement (Bienhaus & Haddud 2018).

Most scientific studies focus on data analytics within supply chains, which is why there is a research gap regarding the topic of this study. According to Nguyen, Zhou, Spiegler, Ieromonachou, and Lin (2018), among scientific publications related to data analytics in supply chains up to 2018, only 11% addressed procurement. Moreover, the majority of studies (38%) examining data analytics adoption and explaining the practical phenomena utilized the resource-based view (RBV) (Arunachalam et al. 2018). However, dynamic capabilities were the second most adopted perspective, used in 19% of selected publications (Arunachalam et al. 2018). In addition to the scientific research gap, there is also a practical need for this topic. Major consulting companies have emphasized in recent reports how analytics will transform business operations and how procurement activities should adapt to future challenges (Deloitte 2020; McKinsey & Company 2016; McKinsey & Company 2020). According to Lasch (2022), procurement managers constantly have to balance cost pressures, driving them to experiment with new technologies and operational approaches. With new technologies, it is crucial to investigate their development to learn from mistakes and enhance these technologies.

This thesis aims to enhance understanding of the utilization and development of data analytics by examining the phenomenon through the procurement function of a service business company. In addition, we strive to provide procurement managers with concrete examples of how data analytics can be developed to improve competitiveness.

1.1 Conceptual framework and key concepts

The conceptual framework of the study is presented below in Figure 1. It illustrates the key concepts of the study and the relationships between them. The conceptual framework helps the thesis address the research questions by first presenting the concepts of analytical capabilities, dynamic capabilities, and data analytics.

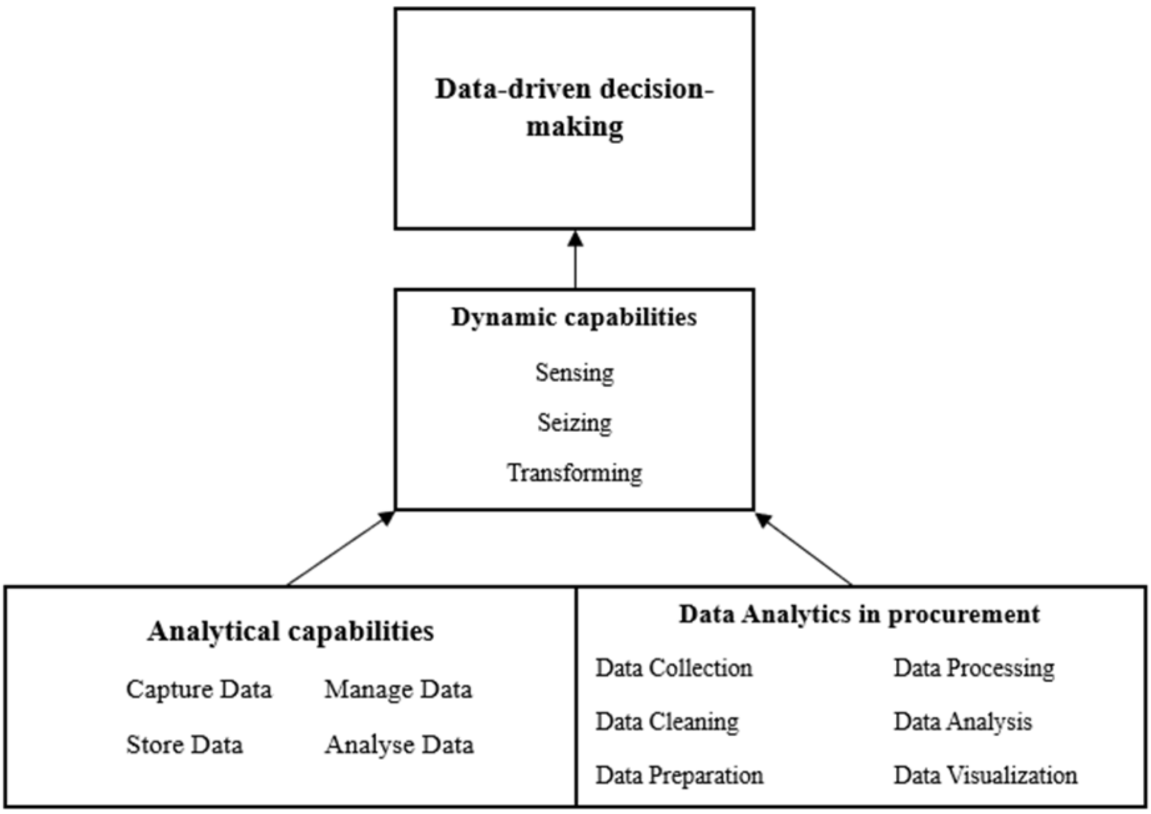

Figure 1. Conceptual framework

Analytical capabilities refer to an organization's ability to collect, store, and process data in such a way that raw data is transformed into information for strategic decision-making. (Medeiros & Maçada 2022).

Big Data refers to "high-volume, high-velocity, and high-variety information assets that require cost-effective, innovative forms of information processing to enhance insight and decision-making" (Gandomi & Haider 2015).

Data-driven decision-making refers to a decision-making process where decisions are based on verified data and its analysis (Rejikumar, Aswathy Asokan & Sreedharan 2020). In data-driven decision-making, verifiable information helps to reduce uncertainty and mitigate potential negative impacts (Poulose, Sharma & Maheshkar 2024, 14-16). The significance of data-driven leadership has grown as the volume of data has increased. For decision-making to be data-based, an organization must cultivate a data-driven culture (Arunachalam et al. 2018). A data-driven culture requires three key components: viewing analytics as a strategic asset, support from top management, and ease of access to information for decision-makers (Arunachalam et al. 2018).

Dynamic capabilities refer to an organization's ability to adapt quickly to changing situations and conditions. Dynamic capabilities consist of three elements: sensing, seizing, and transforming. (Teece 2018)

1.2 Research questions and objectives of the thesis

The aim of this research is to address the gap in the literature regarding the utilization of data analytics in purchasing and supply management, particularly by providing concrete examples of how companies can leverage and develop data analytics in procurement. While data analytics and analytical skills are required throughout the entire supply chain, due to the differences in business functions, this study focuses solely on the supply management perspective. Therefore, other areas of the supply chain are excluded from this work. Additionally, the study concentrates specifically on the service industry from the procurement perspective. To address this theoretical gap and achieve the objectives of this thesis, the following research questions are formed.

The main research question:

Q1: How can data analytics be developed in purchasing and supply management?

Supporting sub-questions:

Q2: How can data analytics be utilized in purchasing and supply management?

Q3: Why is data analytics utilized in procurement?

Q4: How do analytical capabilities and data analytics benefit purchasing and supply management?

Q5: What kinds of barriers exist to utilizing data analytics in procurement?

1.3 Research methodology and limitations

The theoretical part of this study is strongly based on previous literature on the subject. The literature review aims to use a broad selection of articles from various researchers across different years. However, the use of data analytics in purchasing and supply management is an emerging area of research, so there is limited availability of related articles. Therefore, literature on the use of data analytics in supply chains is also utilized in this study to provide a broader perspective.

The empirical part of the study is a qualitative study, chosen due to the nature of the research. Qualitative research is typically used when aiming to gain a deeper understanding of a phenomenon or the meanings behind it. This study specifically addresses the questions of "what" and "how," aiming to provide a broader background to a less-known phenomenon (Eriksson & Kovalainen 2008). The primary data for the study was collected through two semi-structured interviews within the case company.

Given the qualitative nature of the research and its focus on a single case company, it is clear that the study provides only a limited perspective. Therefore, no comprehensive or universal findings and conclusions can be drawn from this research. The following AI applications have been utilized in this thesis: ChatGPT and Grammarly. These AI tools have been used to support creating an overall picture, brainstorming ideas, processing research material, and language and text editing.

1.4 Structure of the thesis

This thesis is structured as follows. The next chapter reviews the literature surrounding key concepts. The third chapter discusses the research methodology. Following this, the fourth chapter presents the results of the empirical study. The final section provides a summary of the research, discusses its limitations, and offers suggestions for future studies.

2 Data analytics in purchasing and supply management

To understand how data analytics can be developed in procurement, it is essential to first comprehend the key concepts of the phenomenon. First, we will discuss the background of data analytics and dynamic capabilities. Additionally, based on the literature, we will examine the benefits and barriers associated with the use of data analytics in organizations. Finally, we aim to understand the impact of analytical skills on the utilization and development of data analytics in companies, as well as the significance of technology and process development in analytics.

2.1 Data analytics

According to Mahanti (2021, 8), data refers to information or facts that are collected for examination, processing, and use to support decision-making. Data is typically either numerical, such as numbers and symbols, or qualitative, such as sound and words (Bhatia & Bansal 2015, 16). For data to be understood, it must have context (Mahanti 2021, 8). Data in itself is of little value unless it is processed and transformed into information. In other words, data is both an interpretation of the objects it represents and an object that must be interpreted. (Bhatia & Bansal 2015, 16; Mahanti 2021, 8) Data analytics exists for this purpose, aiming to process data so that conclusions can be drawn from the information (Mahanti 2021, 134). Data can be utilized through four types of analysis: descriptive, diagnostic, predictive, or prescriptive. Descriptive is the simplest and aims to determine what happened in the past. Like descriptive analytics, diagnostic uses historical data, but it seeks to answer why something happened. Predictive analysis represents more complex analysis, as it uses machine learning algorithms to try to understand what is likely to happen in the future. The most demanding analysis is prescriptive, as it allows for predictions about what will happen next and how to respond to it. In other words, prescriptive analytics answers the question “What should we do?”. (Mahanti 2021, 134-135)

Descriptive process diagrams have been developed for data analytics and data mining, one of the most well-known being the Cross Industry Standard Process for Data Mining or CRIPS-DM (Figure 2). The most critical phase of this process is business understanding, during which the problem is outlined. This step is critical because it determines, for example, the methods for solving the problem and the data to be collected for data analytics. (Provost & Fawcett 2013, 26-28) Once the problem has been outlined, the next step is data identification and collection (Tipi 2021, 44). After data collection, the next phase is data understanding. At this stage, the structure, quality, and characteristics of the data are examined. It is essential to understand what kind of data is available, what deficiencies it has, and whether it is of sufficient quality for analysis. Data visualization can be used at this stage to effectively identify anomalies in the data. (Berthold 2020, 45-53; Provost & Fawcett 2013, 28-29) During the data preparation phase, the data is cleaned, and transformed, duplicates are removed, and missing values are handled. In addition, data is typically combined from different databases or sources to ensure it is of sufficient quality for analysis. (Berthold 2020, 136-149; Provost & Fawcett 2013, 29-30; Tipi 2021, 44) The next phase of the process is modelling. Modelling is a central part of data analytics, as this is where concrete predictive models are created from the data. Modelling typically involves the use of algorithms, regression analysis, and other technologies. (Provost & Fawcett 2013, 31) Before deploying the model, it must be evaluated. In the evaluation phase, the reliability and validity of the model are assessed, and its usefulness is compared against business objectives (Provost & Fawcett 2013, 31). Finally, the model's results are implemented in the deployment phase. This could involve reporting the results or integrating the model into the company's processes. For example, the model could be a predictive model that forecasts future sales. (Provost & Fawcett 2013, 32-34)

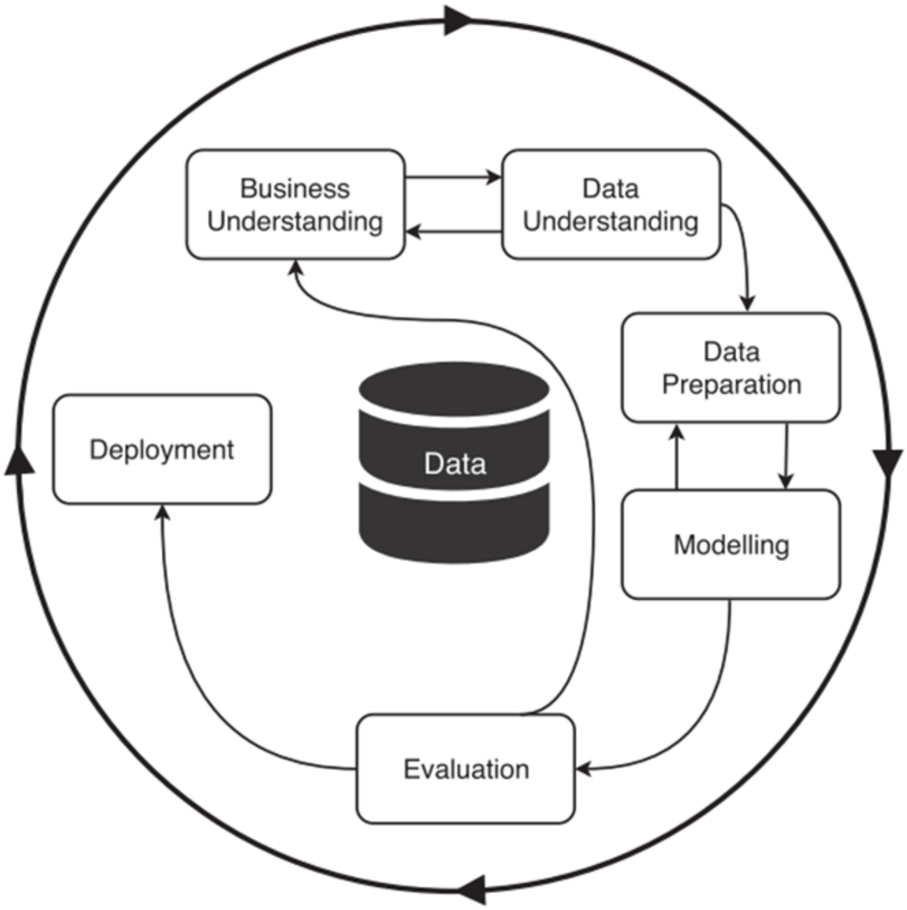

Figure 2: The CRISP-DM process

The volume of data has increased with the proliferation of information and communication technologies (ICT) in supply chain management (Arunachalam et al. 2018). Technologies such as radio frequency identification (RFID), enterprise resource planning (ERP) systems, and the Internet of Things (IoT) have played a central role in the increase and utilization of data (Arunachalam et al. 2018). Data analytics has long been utilized in supply chains, and as a result, numerous researchers have studied its effects, for example, on a company's resilience to business risks (Singh & Singh 2019), logistics (Queiroz & Telles 2018), and social and environmental sustainability (Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba & Roubaud 2019).

Researchers have examined the use of data analytics not only in supply chains but also in procurement in several of their articles. Handfield, Jeong, and Choi (2019) explored the current state and future trends of procurement analytics in their article. According to the researchers, procurement analytics can be divided into both data analytics and cognitive analytics. Data analytics utilizes structured data to address business problems through descriptive and predictive modelling. Typically, statistical methods, graphical visualization tools, and mathematical algorithms are used in data analytics. On the other hand, cognitive analytics employs not only structured data but also unstructured data, from which machine-based learning (MBL) and artificial intelligence produce deeper and more accurate predictions. (Handfield et al. 2019)

2.2 Analytics as a dynamic capability

The growth in data volume and increased use of analytics in supply chain management has recently extended to service business supply chains as well. According to researchers, service-oriented companies, in particular, can significantly benefit from advancements in information technology since they can collect valuable customer data and, by analyzing it, generate higher added value for customers. (Wang, Liu, Liang & Wei 2023) Researchers also suggest that data analytics can drive service innovation, for example, by automating services (Lehrer, Wieneke, vom Brocke, Jung & Seidel 2018).

Dynamic capabilities include sensing, seizing, and transforming. In the sensing phase, the organization's ability to identify changes and opportunities in its business environment is assessed, such as those created by digitalization and technological advancement. During the seizing phase, the organization allocates resources to take advantage of the identified opportunities. In the transforming phase, the organization has adopted and integrated the identified changes. Furthermore, in this final phase, the organization actively seeks to renew processes and business models, thus maintaining competitiveness. (Teece 2018) Figure 3 below illustrates a simplified representation of dynamic capabilities and their connections to business models and strategies. Dynamic capabilities relate to the resource-based view

(RBV), as both theories explain a firm's competitive advantage based on its resources and capabilities (Wójcik 2015). RBV focuses on internal company resources (VRIN), arguing that sustainable competitiveness can be achieved by controlling these resources. In contrast, dynamic capabilities suggest that competitive advantage is maintained through the continuous development of capabilities rather than merely managing existing resources. (Wójcik 2015)

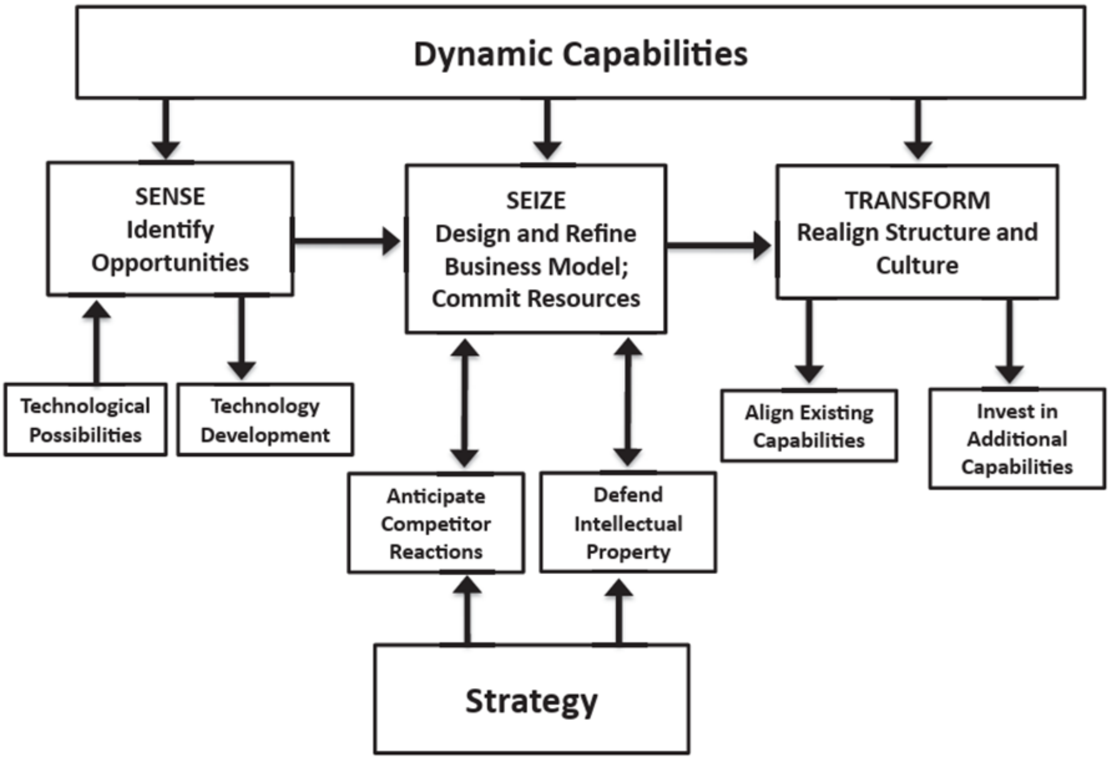

Figure 3. Simplified schema of dynamic capabilities, business models, and strategy (Teece 2018)

Dynamic capabilities require companies to identify and seize opportunities as the business environment changes. Nowadays, technology is evolving rapidly, and markets exist in a hectic environment, which means that companies must be able to proactively adapt and innovate as threats and opportunities arise. (Teece 2018) According to researchers, big data analytics (BDA) presents a new opportunity for companies to achieve competitive advantage

(Wamba, Gunasekaran, Akter, Ren, Dubey & Childe 2017). Competitive advantage also arises from the fact that dynamic capabilities are difficult to imitate (Teece 2018). The adoption of data analytics in companies is linked to dynamic capabilities, as BDA is considered a significant differentiator between high-performing and poorly performing organizations. A strong positive relationship has been found between data analytics and company performance, making data analytics an increasingly important component of corporate decision-making processes. (Wamba et al. 2017) This is because more and more company leaders prefer to make decisions based on data rather than solely on intuition. Companies need to develop resources such as a data-driven culture and organizational learning, which enable the adoption and utilization of data analytics as part of the company's dynamic capabilities. (Almazmomi, Ilmudeen & Qaffas 2022)

2.3 The benefits of data analytics

According to numerous researchers, the utilization of data analytics in procurement and supply chains has significant benefits that companies can achieve. Numerous benefits emerged from the literature, by achieving which companies can develop their competitiveness. The potential benefits of data analytics are summarized in Table 1 below.

Table 1. Perceived benefits of utilizing data analytics

Benefit	Authors
Lower prices and cost savings	Flechsig et al. (2022); Handfield et al. (2019)
Reducing workload and streamlining processes	Bienhaus & Haddud (2018); Flechsig et al. (2022); Handfield et al. (2019); Jain et al. (2024); Karttunen et al. (2023)
Improves decision-making	Albqowr et al. (2024); Bienhaus & Haddud (2018); Justy et al. (2023)
Improved purchasing power	Handfield et al. (2019)
Reduced transactional activity and optimized resource allocation	Handfield et al. (2019); Harju et al. (2023); Justy et al. (2023)
More efficient monitoring and control	Harju et al. (2023); Jain et al. (2024); Justy et al. (2023); Karttunen et al. (2023)
Reduced contract risk	Handfield et al. (2019)
Increased competitiveness	Bienhaus & Haddud (2018); Justy et al. (2023)

One of the key benefits is lower prices and cost savings (Flechsig, Anslinger & Lasch 2022; Handfield, Jeong & Choi 2019). Companies aim for the efficient use of their operations, which is also reflected in procurement organizations. According to Flechsig, Anslinger, and Lasch (2022), procurement managers in private companies, in particular, face cost pressures, leading managers to seek to reduce the number of staff in their procurement departments through new technologies. According to the managers surveyed in the study (2019), lower prices and cost reduction are the main reasons for the adoption of data analytics in companies' procurement processes (Handfield et al. 2019). For example, by analyzing product categories, companies could make more cost-effective procurement decisions. Many companies still cannot obtain detailed cost summaries by category, which hinders procurement organizations from making data-driven decisions. (Handfield et al. 2019)

In addition to financial savings, the utilization of data analytics enhances employee productivity within procurement organizations. According to Handfield, Jeong & Choi (2019), employees have more time to focus on valuable activities. Automating operational functions in procurement using artificial intelligence, big data, and the Internet of Things creates space for more strategic, human-led initiatives (Bienhaus & Haddud 2018). Data analytics, particularly with artificial intelligence, can reduce the workload on individuals (Karttunen, Lintukangas & Hallikas 2023), which would make procurement organizations more efficient. Data analytics can expedite processes by providing statistics and facts at the operational level to support purchasing decisions (Jain, Priyadarshini & Gupta 2024).

As the amount of data increases and business environments become more complex, many organizations have sought to transition toward data-driven decision-making. With data analytics, procurement organizations gain access to facts that support complex decision-making processes (Bienhaus & Haddud 2018). In addition to processes, data enhances decision-making capabilities (Albqowr, Alsharairi & Alsoussi 2024; Justy, Pellegrin-Boucher, Lescop, Granata & Gupta 2023) as well as strategic planning (Albqowr et al. 2024) within procurement organizations. Besides creating data-driven decision-making, data analytics increases a company's purchasing power (Handfield et al. 2019). Purchasing power is particularly emphasized in negotiations with suppliers, which, after the utilization of data analytics, are based on facts (Jain et al. 2024). Fact-based negotiations can lead to reduced inventory levels (Jain et al. 2024) and decrease tied-up working capital (Handfield et al. 2019).

Data analytics can enhance operational procurement by reducing transaction activity (Handfield, Jeong & Choi 2019; Harju et al. 2023). With data analytics, potential resource allocation targets can be identified, allowing for increased order sizes while simultaneously reducing the number of order batches (Justy et al. 2023).

Data analytics improves the reporting of procurement organizations because monitoring is more effective (Jain et al. 2024), and coordination and control are more efficient (Karttunen et al. 2023). Through better monitoring, companies can more effectively track, for example, the fulfillment of service level agreements (SLAs) (Jain et al. 2024) and enhance their understanding of suppliers (Harju, Hallikas, Immonen & Lintukangas 2023), markets (Justy et al. 2023), and customers (Justy et al. 2023).

Other benefits that procurement organizations in companies can potentially achieve through data analytics include reduced contract risk (Handfield et al. 2019), improved competitiveness (Bienhaus & Haddud 2018; Justy et al. 2023), increased accuracy (Bag, Dhamija, Luthra & Huising 2023), and timely availability of materials (Bag et al. 2023; Jain et al. 2024).

2.4 Barriers to utilizing data analytics

There can be challenges in implementing data analytics in companies for various reasons. The key barriers and challenges are summarized in Table 2 below.

Table 2. Barriers

Barrier	Authors
Lack of IT infrastructure and technological resources	Arunachalam et al. (2018); Bienhaus & Haddud (2018); Flechsig et al. (2022); Jain et al. (2024); Joseph Jerome et al. (2022); Moktadir et al. (2019)
Lack of technical skills	Albqowr et al. (2024); Arunachalam et al. (2018); Flechsig et al. (2022); Justy et al. (2023); Perçin (2023)
Data quality and data-related problems	Albqowr et al. (2024); Arunachalam et al. (2018); Jain et al. (2024); Joseph Jerome et al. (2022); Justy et al. (2023); Karttunen et al. (2023); Moktadir et al. (2019)
Lack of top management support and a data-driven culture	Dehkhodaei et al. (2023); Flechsig et al. (2022); Joseph Jerome et al. (2022); Justy et al. (2023); Perçin (2023)
Resistance to change	Flechsig et al. (2022); Jain et al. (2024); Justy et al. (2023)
Lack of training and education	Albqowr et al. (2024); Jain et al. (2024); Justy et al. (2023); Perçin (2023)
Time consuming	Arunachalam et al. (2018)

The utilization of data analytics in procurement can fail even before its implementation within a company. A critical factor is the company's IT infrastructure. According to researchers, the level of IT infrastructure is the most critical challenge (Flechsig et al. 2022; Jain et al. 2024; Joseph Jerome, Saxena, Sonwaney & Foropon 2022; Justy et al. 2023; Moktadir, Ali, Paul & Shukla 2019) that companies face when it comes to data analytics. In addition, a general lack of resources slows down or even prevents the adoption of data analytics (Arunachalam et al. 2018). On the other hand, a company's IT infrastructure may be advanced, but the lack of data analytics tools (Justy et al. 2023) or processes (Arunachalam et al. 2018) can become the main issue.

Another key challenge is the lack of skills (Arunachalam et al. 2018). Researchers highlight the absence of employees with data analytics expertise within the company's workforce as a particular issue (Justy et al. 2023). According to Albqowr, Alsharairi, and Alsoussi (2024), the general lack of technical skills complicates the integration of data analytics into the company's processes. Insufficient technical skills can lead to issues such as increased resistance to change or delays in leveraging analytics in procurement. (Albqowr et al. 2024)

Barriers and challenges can also arise at later stages, which negatively affect the use of data analytics. In supply management and purchasing, data is collected from multiple sources (Wang, Gunasekaran, Ngai & Papadopoulos 2016), which increases the likelihood of potential obstacles. The quality of data analytics in procurement is often diminished by poor data quality (Arunachalam et al. 2018; Jain et al. 2024; Justy et al. 2023; Moktadir et al. 2019). Data can also suffer when information is transferred manually between systems (Karttunen et al. 2023). Data collected from multiple sources may cause problems during the integration phase (Moktadir et al. 2019), as the data may exist in various formats. According to Justy et al. (2023), the large amount of data can slow down the utilization of data analytics. In addition, incorrect or insufficient data recording during the data collection or analysis phase can complicate analysis (Albqowr et al. 2024). Challenges may also arise from inadequate investments in the company information system security and data confidentiality (Joseph Jerome et al. 2022).

Implementing new technologies or processes in companies typically requires the support of top management. This also applies to the adoption of data analytics. (Flechsig et al. 2022; Justy et al. 2023; Perçin 2023) Weak support from top management for the adoption of new technologies slows down their implementation in organizations and, in the worst case, can completely halt the utilization of new technologies in companies (Dehkhodaei, Amiri, Farsijani & Raad 2023). A lack of leadership that supports data analytics (Justy et al. 2023) can result in insufficient funding being allocated to it, which may hinder the adoption of new technologies (Dehkhodaei et al. 2023). Insufficient or limited funding may stem from the perceived uncertainty surrounding the benefits and returns of investing in data analytics (Joseph Jerome et al. 2022). Another challenge may be the absence of data-driven decision-making within the organization, which can lead top management to withhold their support for using data analytics (Dehkhodaei et al. 2023).

Even if a company's top management supports the use of data analytics in procurement, it may face resistance from employees (Karttunen, Lintukangas & Hallikas 2023; Jain, Priyadarshini & Gupta 2024). Employees may have low motivation toward adopting newer technologies and their potential utilization (Jain et al. 2024). According to Jain et al. (2024), overcoming resistance to change requires a mindset shift across the entire organization. In particular, the lack of a supportive culture (Flechsig et al. 2022) and poor alignment of technology with the organizational culture (Jain et al. 2024) increase resistance to change within the organization. Even if resistance to change is overcome, there is still a risk of employees deliberately slowing down the adoption of the new process (Joseph Jerome et al. 2022).

The final key challenge in implementing and utilizing data analytics is the difficulty of training employees. If employees lack sufficient technical or analytical skills, training to improve their competencies can lead to significant costs (Jain et al. 2024). Resistance to analytics among employees (Albqowr et al. 2024) and the organization's limited readiness to train its workforce (Perçin 2023) can also pose challenges. Even if the capacity for employee training exists, a lack of training resources may become a barrier (Joseph Jerome et al. 2022). Other reasons for negative reactions toward data analytics in organizations include gaps in understanding its requirements, capabilities, and benefits (Joseph Jerome et al. 2022). In addition, utilizing data analytics requires time, which can be a barrier for some organizations (Arunachalam et al. 2018).

2.5 Developing analytical capabilities

The adoption of new technology or processes does not always directly enhance organizational performance and may instead cause confusion and problems for adopters. This is often due to the lack of an analytical culture in the organization. (Handfield et al. 2019) A similar situation can occur when implementing data analytics in procurement. At the organizational level, analytics capabilities consist of three entities: data-driven decision-making, a collaborative environment, and organizational adaptability (Öhman, Arvidsson, Jonsson & Kaipia 2021). According to Dubey, Gunasekaran, and Childen (2019), analytics capabilities, like data analytics itself, are dynamic capabilities that provide a competitive advantage to companies. Research shows that top-performing organizations use analytics in their business operations up to five times more than poorly performing organizations (Dubey, Gunasekaran & Childen 2019). Therefore, procurement professionals are expected to possess analytical skills (Handfield et al. 2019), which are among the most critical strategic competencies for procurement professionals (Karttunen 2018). On a practical level, analytical capabilities refer to an organization's or individual's ability to capture, store, manage, and analyze data (Clain, Liberatore & Pollack-Johnson 2016).

Developing analytical capabilities is essential for organizations aiming to effectively utilize data analytics. One fundamental aspect is fostering a data-driven culture within the organization. (Arunachalam et al. 2018) The absence of a data-driven culture undermines the use of data, as employees are not motivated to leverage it (Almazmomi et al. 2022). A data-driven culture is an "intangible resource representing people's beliefs, attitudes, and opinions toward data-driven decision-making" (Arunachalam et al. 2018). Thus, its development within organizations requires more than just financial resources and advanced technologies. A data-driven culture can be promoted in three ways: the organization must treat analytics as a valuable and strategic asset, top management must support the data-driven culture, and the organization must utilize analytics while basing decision-making on data (Arunachalam et al. 2018). However, achieving a fully data-driven culture within an organization is impossible without involving the entire supply chain (Arunachalam et al. 2018). Therefore, it is important to consider suppliers and customers when advancing a data-driven culture.

The level of data-driven culture can be assessed using various frameworks. In the framework below (figure 4), researchers have classified data-driven culture into four stages: initiation, adoption, and routinization stages (Arunachalam et al. 2018). In the first stage of developing data analytics and analytics capabilities, organizations often have little data and insufficient analytics (Arunachalam et al. 2018). In other words, in the initiation phase, the organization's data management is at a weak level, leading to ineffective use of data. There are two types of adoption phases, depending on the organization's capabilities: 1) either there is a lot of data, but it cannot be used, or 2) there is little data, but it can be utilized with advanced analytics (Arunachalam et al. 2018). A data-driven culture is fully integrated into the organization when it reaches the routinization phase. At this stage, the organization has abundant data, and it can analyze it with advanced analytics. (Arunachalam et al. 2018)

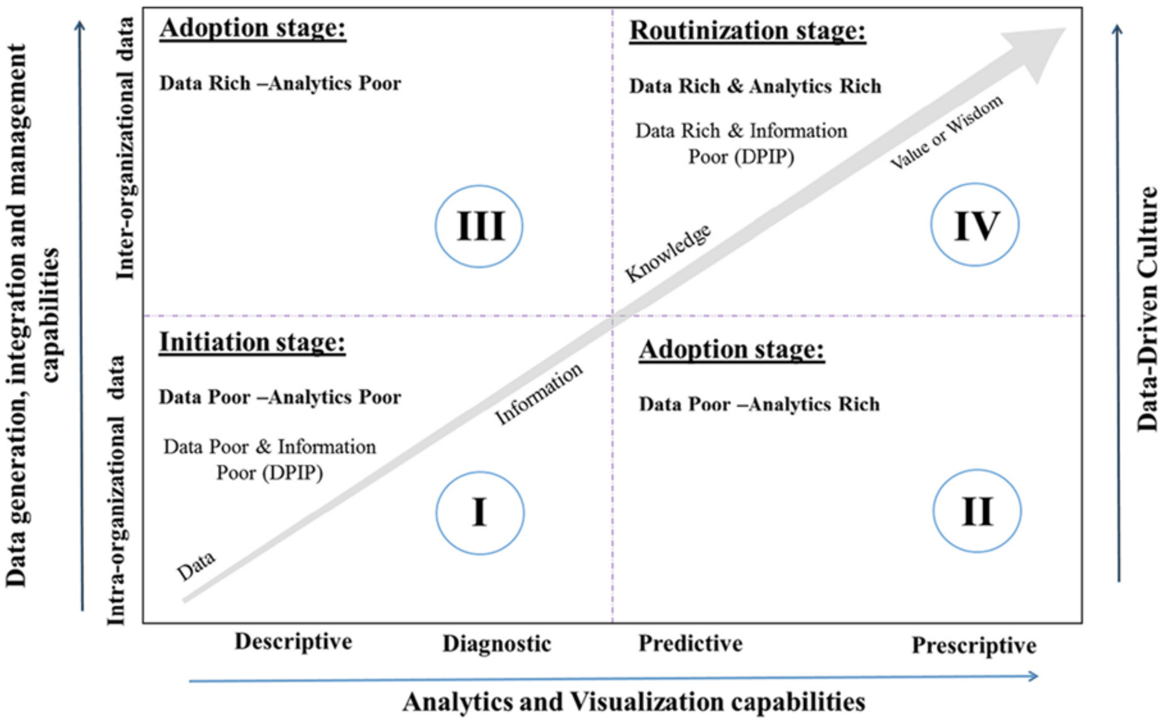

Figure 4. BDA capabilities framework for a supply chain (Arunachalam et al. 2018)

In addition to fostering a data-driven culture, it is crucial to promote organizational learning, as this enables the creation and development of employees' analytics readiness (Almazmomi et al. 2022). Handfield et al. (2019) encourage organizations to build a culture of "learning by doing". It is particularly important for managers to encourage experimentation, for the organization to tolerate failures, and for new insights to be implemented in practice (Handfield et al. 2019). Organizational learning can lead to continuous improvement (Kokkinou, Kollenburg & McDermott 2024). An organization can enhance its processes, but first, it must understand where improvements are needed. In other words, the organization must be able to collect data, understand it, and ultimately develop processes based on the insights gained. According to Kokkinou et al. (2024), a culture of continuous improvement in an organization significantly develops data analytics capabilities.

In companies, employees' analytical capabilities can be enhanced not only through a data-driven culture, organizational learning, and continuous improvement but also by selecting user-friendly technologies and ensuring data quality (Arunachalam et al. 2018).

2.6 Developing data analytics in technology and processes

The development of data analytics in organizations does not progress solely by improving the analytics capabilities of the staff. Advanced systems and tools are required to enable data analytics to be utilized in businesses. Digitalization has made it possible to develop various technologies, starting with the development of enterprise resource planning (ERP) systems. In the 1990s, the first ERP systems began to emerge, which covered virtually all areas of a company, from production to human resources management (Robert Jacobs & Ted Weston, 2007). As a result, the importance of ERP systems has grown as they contain diverse data. The development of ERP systems has also accelerated the digitalization of procurement (Karttunen et al. 2023). According to Handfield et al. (2019), conventional ERP systems serve as the foundation for organizations' analytics in addition to the aforementioned functions. This is because basic data analytics relies on the use of historical data, which the ERP system has gathered over time. (Handfield et al. 2019)

In order to develop data analytics within organizations, it is necessary to advance not only the employees but also technology and processes. Altundag and Wynn (2024) have developed diagrams that can help determine the stage of a company's data analytics development (Figure 5). There are four stages: basic level, intermediate level, standardised level, and transformed level. In addition to assessing their data analytics dimension, companies can use these diagrams to develop their analytics. (Altundag & Wynn 2024) When companies begin to use data analytics as part of their business, such as in procurement, the use of ERP systems becomes prominent (Altundag & Wynn 2024). At the basic level, ERP systems utilize primarily historical data (Handfield et al. 2019), which is used for descriptive analytics (Altundag & Wynn 2024). Moving from basic data analytics to a more advanced approach requires companies to invest in analytics tools and consider adopting advanced technologies. For example, business intelligence (BI) tools, machine learning, artificial intelligence, and robotic process automation are essential for developing data analytics (Arunachalam et al. 2018). By automating data collection, the reliability of data can be improved (Altundag & Wynn 2024), and this data can be processed with advanced analytics tools to generate prescriptive analysis for the future. In addition, it is important to integrate analytics across the organization to ensure that raw data becomes reliable and is continuously available (Altundag & Wynn 2024). When developing technological solutions, the visual representation of analytics must be considered to ensure that even complex information is presented in a simpler form. BI tools enable this, as their purpose is to combine data from various sources, automate reporting, and improve the accuracy of forecasts (Arunachalam et al. 2018).

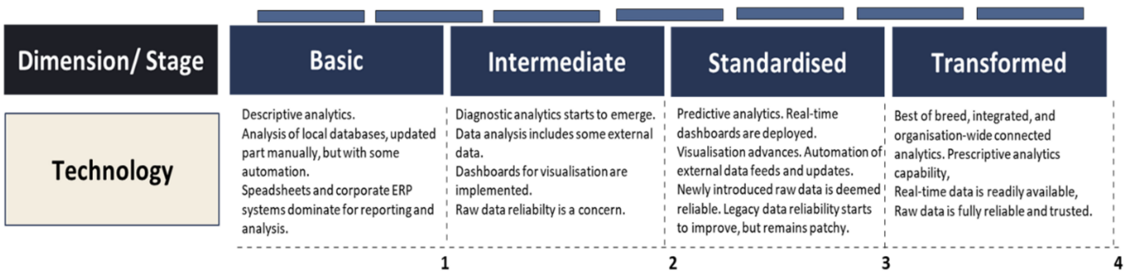

Figure 5. Maturity model stage descriptions by technology dimension (Altundag & Wynn 2024)

Developing data analytics in procurement also requires the development of processes to fully leverage new tools and technologies (Figure 6). According to Altundag and Wynn (2024), the first step is to recognize procurement as a strategic function. If procurement is classified as merely a support function within a company, it becomes nearly impossible to develop procurement effectively (Altundag & Wynn 2024). It is particularly critical to classify procurement processes and implement them as agreed. This way, the quality of data can be improved, and processes can be automated (Altundag & Wynn 2024). The researchers also emphasize that analytics must be integrated into procurement processes, which enhances data-driven decision-making within the company. As companies systematically develop their procurement processes, they eventually end up automating them almost entirely through robotics. However, developing procurement processes requires technology to be advanced simultaneously, so that data analytics and robotics can be integrated into the processes. (Altundag & Wynn 2024)

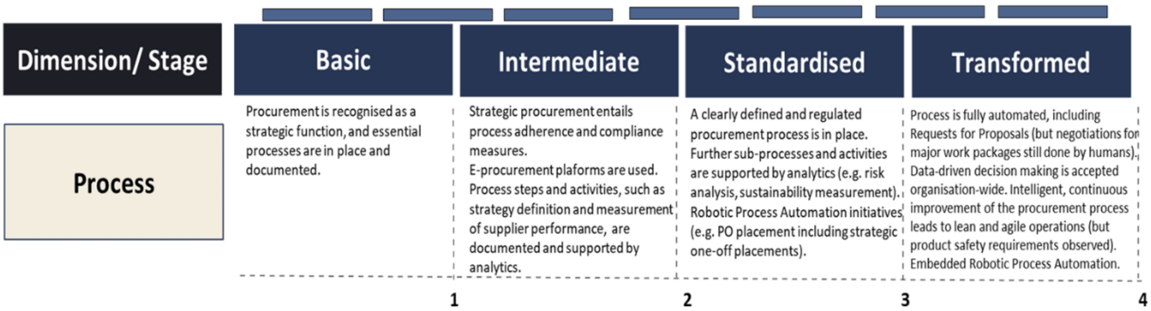

Figure 6. Maturity model stage descriptions by process dimension (Altundag & Wynn 2024)

3 Methdology

This chapter presents the research methodology of the thesis. The research methodology describes how the empirical part of the study was conducted and explains the data collection process. In addition, a brief description of the case study is provided. Finally, we critically evaluate the reliability and validity of the thesis.

3.1 Qualitative research

The purpose of qualitative research methods is to understand reality by interpreting it. Qualitative research is particularly relevant when there is limited information about the phenomenon being studied. (Eriksson & Kovalainen 2008, 4-6) The research method for this thesis is a case study, which is one of the most commonly used qualitative research methods (Eriksson & Kovalainen 2008, 6). Case studies allow for presenting complex and difficult-to-understand phenomena in an accessible and practical form (Eriksson & Kovalainen 2008, 116). This case study focuses on a single case to gain a deeper and more detailed understanding of the subject being studied. According to Voss, Tsikriktsis, and Frohlich (2002), a single case study allows for a deeper analysis compared to multiple case studies. Some concerns have been raised regarding case studies, which must be taken into account when conducting a case study. A key challenge is that case studies often lack research rigor due to procedures not being strictly followed (Yin 2003, 14). This can lead to biased or incorrect interpretation of results. Another challenge is the generalizability of case studies (Yin 2003, 15). Often, results from a case study cannot be directly applied to other cases, although generalizations can still be made. In practice, the primary aim of case studies is to expand and generalize theories rather than to produce representative results (Yin 2003, 15).

In qualitative research, interviews, surveys, observations, and textual data are commonly used as data sources. In qualitative research, interviews are divided into three categories:

structured, semi-structured, and unstructured. Most qualitative interviews are semi-structured, where the aim is to explore the phenomenon or subject using “what” and “how” questions. The advantage of semi-structured and guided interviews is that the material collected from them is systematic and comprehensive, even though the interviews are typically quite conversational and informal. (Eriksson & Kovalainen 2008, 77-83) A case study focuses on current events while relevant behaviour cannot be manipulated. One of the key strengths of a case study is its ability to handle various types of evidence, ranging from documents to interviews. (Yin 2003, 8-11)

3.2 Data collection

The data for this study was collected through semi-structured interviews, aimed at confirming the results observed in the literature review and contributing to the theory in the field. In addition, the interviews sought to explore how the use of data analytics in procurement could be developed in the future. A total of two interviews were conducted in November 2024. The interview questions are presented in Appendix 1. The table below (Table 3) provides further details about the interviews conducted in the study.

Table 3. Details of the interviews

Letter	Interviewee	Length
A	Sourcing Director	90 minutes
B	Procurement and Logistic Manager	38 minutes

The interviewees were selected in advance to ensure that participants knew and understood the topic sufficiently. Interviewees were selected for the following reasons: 1) they possess the broadest expertise within the case company regarding the research topic, from strategic procurement to operational procurement, 2) they have access to information relevant and critical to the study, and 3) the research schedule and limited resources. According to Tuomi and Sarajärvi (2009, 85), qualitative research does not aim for statistical generalizations, which is why it is critical that the interviewees know as much as possible about the phenomenon being studied. As a result, the interviews provided diverse and in-depth data, which could be analyzed in the research. Before the interviews, the interviewees were sent interview questions, allowing them to familiarize themselves with the interview themes. The interviews included five themes: background, data analytics, motivations, challenges, and the future. The interview themes were constructed based on the research questions and previous literature, ensuring that the data gathered was comprehensive regarding data analytics. The interviews conducted served as the primary data for this thesis. In addition, data collected during previous research was used in the analysis, but this data served as secondary and only expanded the author's overall understanding.

3.3 Data analysis

Qualitative case studies can be analyzed using various methods, with common ones including content analysis, critical incident analysis, and conversation analysis (Eriksson & Kovalainen 2008, 130). In this thesis, the data was analyzed using content analysis. The theme interviews had predefined themes, according to which the data was categorized. In addition to the predefined themes, emerging themes from the interviews were also analyzed.

The quotes presented in the study have been translated into English, as the interview data was in Finnish. The analysis of the research material began by familiarizing oneself with the collected data and outlining preliminary themes. After this, all information that could identify the interviewees or the case company was removed from the data. In the qualitative analysis of the research data, the AI application ChatGPT was utilized to support the author's analysis. This application used content analysis, enabling the identification of both predefined and emerging themes within the data. In addition, ChatGPT assisted in outlining the structure of the analysis. However, the author conducted the analysis independently, and AI applications were not otherwise utilized during the analysis phase.

3.4 Case description

The case company in this study is a Finnish maintenance service provider specializing in various cooling solutions and professional kitchen equipment maintenance. The company is a significant player in Finland, employing over 300 people. The name and other details that could potentially identify the case company have been withheld for confidentiality reasons.

In recent years, the case company has recognized the importance of data analysis and data-driven decision-making, which has led to an increased focus on analyzing data. Although data analysis and data-driven management have been implemented throughout the organization, this study focuses solely on the case company's procurement organization. The procurement organization consists of the sourcing director, procurement and logistic manager, purchasing manager, and buyers. The procurement organization works closely with the case company's warehouse organization, which is integrated with procurement. This is reflected in the fact that the procurement and logistic manager supervises both buyers and warehouse employees. The procurement function is responsible for ensuring that the company's operational activities run smoothly, which involves sourcing equipment, spare parts, and various chemicals. In addition to operational procurement, the procurement organization is responsible for managing the company's items in the enterprise resource planning (ERP) system. Therefore, procurement must regularly verify and update the item data, which increases the procurement organization's influence on the company's data analytics.

3.5 Reliability and validity

Four different tests are commonly used to assess the quality of empirical social research. Case studies represent one form of this research, thus making these tests applicable to case studies as well. (Yin 2003, 40) Since this thesis is a case study, these tests are employed to evaluate its quality. The four tests are construct validity, internal validity, external validity, and reliability (Yin 2003, 40–41).

Reliability refers to the extent to which research procedures, such as data collection, can be repeated to yield the same results each time (Yin 2003, 40). In other words, reliability reflects the consistency and reproducibility of research outcomes. In qualitative research, reliability primarily depends on how transparently and systematically the research data has been collected, documented, analyzed, and interpreted (Yin 2003, 45). In this study, reliability was improved through a clear analysis process, triangulation, and precise interviews. The interview data was transcribed and later analyzed using the ChatGPT AI application. The AI application utilized content analysis and was used solely to support the analysis. It outlined themes from the data, which the author then independently analyzed. This approach ensured a systematic and data-driven analysis, reducing potential biases related to the author's subjective interpretations. Additionally, the scope and depth of the data were ensured using data triangulation and methodological triangulation (Tuomi & Sarajärvi 2009, 143–146). Reliability was further supported through semi-structured thematic interviews. Addressing predefined themes, as well as emerging topics during interviews, deepened responses and expanded the research subject. However, reliability could be limited by factors such as a small sample size, respondent bias, or subjective analysis. A small sample size limits the generalizability of the thesis, potentially resulting in insufficient findings. Respondents might provide socially desirable answers instead of genuine responses (Hirsjärvi, Remes & Sajavaara 1997, 206). Additionally, as the analysis depends on the researcher's interpretation, a different researcher could theoretically draw alternative conclusions. These limitations were minimized by incorporating secondary data, using a structured interview method, and analyzing data objectively. It should be noted that the author of this thesis has previously been employed by the case organization. While the results are reported objectively, it must be acknowledged that the author's personal experiences from working at the case company could potentially influence the interpretation of the findings.

In addition to reliability, it is essential to understand validity, meaning how accurately a study measures what it aims to measure (Yin 2003, 40). Construct validity assesses how well the study's concepts and measurements align with the phenomenon under investigation (Yin 2003, 40–42). In this thesis, construct validity was ensured by purposefully selecting interviewees, thereby securing diverse viewpoints. The study applied an inductive, data-driven approach complemented by a theory-guided approach. This enabled the integrating of findings into existing research. Internal validity refers to how accurately the study explains the investigated phenomenon without interference from external factors (Yin 2003, 42–43). Internal validity was pursued through consistent interview questions and a clearly defined analysis process. Interview questions, based on previous literature, ensured relevance to research questions. External validity concerns the generalizability of research findings (Yin 2003, 40). Due to the nature of this study, generalizability is limited. Limitations arise from the focus on a single company, the number of interviewees, and the industry in question. Consequently, findings from this thesis cannot be generalized across other organizations or industries. Procurement processes, for instance, may significantly differ across industries and organizations. Nevertheless, results can be compared with other studies and, after contextual consideration, cautiously applied to organizations within service-oriented businesses. Additional validity-related limitations include restricted interview questions, limited data, and temporal scope.

4 Results and analysis

This chapter presents the empirical phase of the study, where the content of the interviews is reviewed through analysis. First, the general attitude of the case company toward data analytics and its significance in decision-making and management is examined. Next, we analyze the use of data analytics in the company's procurement organization. In addition, the empirical phase explores the challenges and benefits of using data analytics, the culture of the case organization, and the analytical capabilities of its employees. Finally, we analyze how the company could improve the utilization of data analytics in procurement.

4.1 The role and importance of data analytics in the case company

In both interviews, the strategic importance of data for the company was emphasized. Data analytics is particularly seen as a tool to support strategic decision-making. However, this has not always been the case. The amount of data has grown exponentially, and this phenomenon has also impacted the case company. The interviews reveal that decision-making was previously largely based on intuition and experience. While data was available, its use was limited. Moreover, data-driven management had not yet been fully adopted at that stage. At this stage, initial signs of utilizing dynamic capabilities have emerged. In practice, the case company has identified changes in its business environment as technology has advanced at an accelerating pace over the years.

"Previously based on experience and intuition, but more and more, the company is being steered toward data-driven management and decision-making based on knowledge." – Interviewee A

As the company transitioned to digital systems, such as an enterprise resource planning (ERP) system, the founders considered the growing importance of data in the future. In other words, the founders saw data and data analytics as a potential enabler of competitive advantage when selecting the ERP system for the company. The company recognized the need to develop analytics, representing dynamic capabilities. In the sensing phase, the founders were clearly driven by the need for a data-driven culture, which would differentiate the case company from its competitors and thus enhance its competitiveness. The sensing phase is also evident in the company's decision to implement an ERP system. However, the interviews revealed that the use of the ERP system was limited in its early stages, which prevented the company from fully leveraging the data for several years. This began to change about a year ago when the company's top management decided to shift from intuition-based decision-making to data-driven management. The decision to shift from intuition-based to data-driven management indicates a transition from the sensing phase, where opportunities are identified, to the seizing phase, where those opportunities are leveraged. Over the past year, the role of data analytics has grown significantly, with numerous training sessions organized for managers and the importance of data-driven leadership emphasized to middle management. The seizing phase of dynamic capabilities is evident in the case company's investments in developing analytics skills. Training has been the organization's primary method for updating employees' competencies in analytics and data utilization.

"Data-driven management was decided by the top management already a year ago, with the understanding that we can no longer rely on gut feeling but must focus increasingly on data-driven management." – Interviewee B

The management of the case company not only supports the development of analytics but has actively encouraged the entire organization to adopt data-driven decision-making. The seizing phase of dynamic capabilities fundamentally involves recognizing and leveraging opportunities by developing the business. This includes investments, strategic-level decisions, and resource reallocation. In addition to training programs, the company has hired a consultant whose role is to enhance the company's ability to produce higher-quality reports and improve trust in the data. Without strategic-level decisions, resources likely would not have been allocated to hiring a consultant, which aligns with the seizing phase of dynamic capabilities. The main challenge within the organization has been extracting data from the system and understanding the data.

"There is a lot of data in the ERP system, but we've had challenges getting that data out — if three different guys extract the data, you'll get three different answers." – Interviewee B

The role of data analytics in the company's procurement function has also grown in recent years as more historical procurement data has been extracted from the ERP system. According to the interviewees, data analytics serves as both a reactive and proactive tool in procurement. According to Interviewee B, neither aspect is emphasized more, as analytics is used equally for both purposes.

"Of course, we look at the past to see what we've done and make adjustments to practices if there's something that needs fixing. And proactively, we try to, for example, prevent certain issues from occurring." – Interviewee B

4.2 Current data analytics practices

The case company has begun investing in utilizing analytics as part of daily operations. As already mentioned, the use of data analytics in procurement is both reactive and proactive. In the case company, reactive analytics is used to identify past errors and solve problems. According to Interviewee A, this is applied, for example, when investigating the causes of complaints and addressing challenges in inventory turnover. In addition, the interviews highlighted the identification of anomalies in purchasing behaviour.

"And it has been noticed that, after discussing the matter and showing the buyers the values, purchasing behaviour has changed – moving more toward the set goals." – Interviewee B

Data analytics is also used proactively in procurement, supporting the anticipation of future needs and the planning of procurement strategies. In the case organization, for example, purchase volumes are monitored, which can be leveraged to achieve better negotiating positions.

The interviews reveal that the use of data analytics has been integrated into the daily operations of procurement. Both interviewees regularly use analytics as part of their work. The usage is weekly, driven by various weekly reports and monitoring activities. While both interviewees emphasize that the use is primarily consistent, analytics is also occasionally utilized on a project-specific basis. This is, for example, due to strategic supplier negotiations, for which data is not analyzed on a regular basis.

The procurement organization of the case company uses the company's ERP system and Microsoft Excel for analytics. The ERP system is the primary source of data since all company information flows through it. The procurement organization collects data on, for example, buyers, suppliers, inventory, and purchases. Interviewee A emphasizes that this type of data is primary data, which is used alongside daily tasks. Secondary data is also collected but is mainly used to support the primary data. Interviewee A mentions market data and statistics as examples of secondary data. In other words, the case company's ERP system enables the collection and manipulation of extensive and diverse data. The ERP system allows basic filtering and editing of data, making it possible to generate direct reports without separate analytics tools. However, according to the interviewees, the system has limitations, which is why data is typically extracted from the ERP system and processed separately in Excel.

"But all the data comes from the ERP system, and it's modified in Excel. We don't have any other external software." – Interviewee B

Raw data is extracted from the ERP system and analyzed using Excel. Data analytics has been used in the procurement organization for tasks such as supplier comparisons, ABC analysis, complaint management, and monitoring purchase invoices.

4.3 Challenges in the case company

Typically, when new systems or practices are implemented in organizations, various challenges arise that affect their adoption and utilization. The case company has also identified several challenges associated with the implementation of data analytics. The interviewees emphasized issues with data quality and availability as the most significant challenges related to data analytics. Poor or inaccurate data quality can significantly hinder the work of the procurement organization in the long term, as future needs cannot be effectively analyzed, or the analysis may lead to incorrect conclusions.

"If it's inaccurate or you can't trust it, you become uncertain. Or if it's incorrect, you end up making wrong decisions." – Interviewee B

The potential errors in data have a greater impact on strategic and tactical procurement in the case company, rather than on operational procurement. This is because analytics in the case organization is primarily used as a tool for decision-making and supporting management rather than for managing daily routines. The interviews revealed that data quality also suffers due to the actions of the case company's employees. Some procurement activities do not follow the established processes, which means that no trace is left in the ERP system, and consequently, no data is available for later analysis.

"Not all purchasing transactions leave a trace. If all purchasing activities do not follow the process, a margin of error arises." – Interviewee A

In addition to uncertainty regarding data quality, challenges with data availability were also identified. Data required for analytics must be extracted from the ERP system, which increases the likelihood of risks. Sometimes, multiple data files are needed for analysis, and these files have not yet been configured in the ERP system. Issues with data availability primarily cause time losses in the case organization, as employees must create custom reports containing the appropriate data for analysis.

In addition to data-related challenges, technological challenges also arise in the case company. The addition of various development projects and changes to the ERP system is slow, which limits the utilization of data analytics. For example, the procurement organization cannot implement desired metrics that are needed for strategic development. As mentioned earlier, the ERP system does not fully support data analysis and reporting, which is why these activities are conducted in Excel. The interviewees have recognized the need for advanced technologies, such as artificial intelligence, but these have not been widely adopted. As technologies continue to evolve, it is crucial for the case company to explore the opportunities and risks they present and integrate them into its processes when necessary. Otherwise, the limitations of current systems and the lack of advanced technologies could become a critical issue for the case company in the long term, as the company risks losing its competitive edge.

Technological challenges can be avoided by investing in new technological solutions, but issues may arise from the skill levels of the staff. The interviews revealed that employees' analytics skills vary, which, in turn, slows down the adoption of data-driven decision-making. The procurement organization uses only the ERP system and Excel, but proficiency with these tools also varies. No specific training on these systems has been provided to the staff.

"None of us have been trained in the ERP system; it's been more of a so-called self-learning model." – Interviewee A

Trainings have been organized, but primarily for managers. These have covered topics such as artificial intelligence and data-driven leadership. However, no training has been provided on the ERP system or data processing, which increases the likelihood of, for example, inaccurate analyses. Additionally, insufficient analytics and IT skills slow down employees' work, which manifests as inefficiency.

For the entire organization of the case company to understand the role of data analytics and the importance of data-driven leadership for competitiveness, both employees and management need to maintain a neutral attitude toward new developments. The interviews strongly highlighted that management supports the utilization of data analytics in procurement. Additionally, management aims to increase data-driven decision-making throughout the organization. However, a potential challenge lies in resistance to change, which could hinder the adoption of new practices and processes. In the case company's procurement organization, significant resistance to change has not been observed, but there have been challenges. Attitudes toward data analytics have become more positive, although some employees still exhibit resistance to change. The interviews, however, revealed that this resistance has diminished over time and does not directly affect employees' daily work.

"There has been some resistance within the team, but as things have been better understood, the attitude has shifted in a more positive direction, and now there's even a growing desire for more data." -Interviewee A

In addition to resistance to change, challenges may arise if all employees do not understand the opportunities created by utilizing data. For example, in the case company, technicians are not directly involved with analytics, which can create challenges. Employees may, for instance, bypass processes because they see no direct benefit for themselves. This can make it more difficult to integrate analytics into the entire organization.

In addition to the previously mentioned challenges, issues can arise when processes are not followed. According to Interviewee A, problems occur in projects because purchases made directly for them are not registered in the ERP system. This distorts the data, which can lead to incorrect procurement decisions in the future. The case company's procurement organization collects data from various sources, such as suppliers, the internet, and markets. Inputting this data into the ERP system is mainly done manually, which increases the likelihood of input errors. However, this is not a major issue, as one of the procurement organization's tasks is to update and maintain item data. This ensures that errors are eventually corrected.

The barriers and challenges that emerged during the interviews are summarized in the table below (Table 4), which also provides a brief description of each.

Table 4. Challenges and barriers identified in the interviews

Barrier and challenge	Description
Data quality and availability	Data inconsistencies and missing records reduce the reliability of analytics and hinder decision-making.
Non-compliance with processes	Not all procurement activities follow established processes, leading to gaps in data collection and analysis.
Lack of advanced technologies	Limited use of AI, automation, and predictive analytics prevents the procurement function from leveraging data fully.
Slow development of the ERP system	ERP system updates and enhancements are slow, making it difficult to integrate new analytics features.
Fragmentation of employees' analytics capabilities	Employees have varying levels of analytics skills, creating inefficiencies in data usage and decision-making.
Lack of IT training	A lack of structured IT and data analytics training results in insufficient knowledge of tools and techniques.
Slow attitude change and resistance to change among employees	Some employees are resistant to adopting new data-driven approaches, slowing the cultural shift towards analytics-based decision-making.

4.4 The benefits of data analytics

The implementation of data analytics has brought significant benefits to the case company and its procurement organization. Benefits have been observed in both operational and strategic procurement. The interviewees agree that data analytics has simplified, enhanced, and optimized their work. Analytics has increased efficiency in procurement processes. For example, the monitoring of purchase invoices has streamlined the work of buyers, and the number of unprocessed invoices has remained low since the monitoring began. In addition, analytics has improved the tracking of inventory turnover. The adoption of data analytics has also reduced the number of errors, as decisions are now based on facts rather than intuition.

"Now that we have the data, we can show them how they've done things – we're not monitoring them closely – but we can keep track." – Interviewee B

Reviewing data also helps managers identify employees' mistakes and correct misunderstandings. With the help of numbers and facts, the procurement organization has learned from mistakes, which is credited to data analytics.

"Yes, the quality has improved, as it helps with monitoring, for example, and even the practices have changed." – Interviewee B

In addition to operational benefits, strategic-level benefits were highlighted in the interviews. Data analytics has improved decision-making within the procurement organization. Instead of relying on intuition, the development of procurement strategy is now based on data, which reduces the likelihood of risks. According to Interviewee B, data analytics enables better decision-making by allowing for additional analysis when needed.

"Now that you have some data as a foundation, you can trust your actions more." – Interviewee A

In addition to decision-making, analytics has enabled a better negotiating position. With concrete numbers, it is possible to negotiate better discounts, payment terms, and warranty conditions with suppliers. Analytics allows negotiations to go beyond individual supplier purchases by bringing data for the entire product category into the discussion, which can motivate the supplier. Strategic benefits can also be seen in forecasting future trends, as proactive analytics enables anticipation of upcoming market trends. According to the interviewees, the quality of procurement has improved, for example, through product grouping, as supplier comparisons can now be conducted more systematically.

"With its help, different suppliers and various equipment or spare part brands can be compared efficiently, enabling the best technical and commercial choice." – Interviewee A

In the case company, quality measurement is based on monitoring complaints, as the company does not manufacture any products itself. Analytics has been used in complaint tracking, enabling efficient responses to issues. In addition, according to Interviewee A, suppliers have previously been scored using data. With analytics, suppliers can be evaluated effectively and comprehensively, taking into account factors such as prices, delivery times, quality, and payment terms. This ensures that the procurement organization can provide the customer with the best technical option while the company makes the best commercial choice.

Data analytics has also enabled the case company to perform ABC analysis, allowing the procurement organization to focus on the most critical spare parts and equipment for the company. Interviewee A emphasizes that data analytics has provided business benefits. Through analytics, cost savings have been achieved, which supports the company's strategic goals and, in the long term, can improve competitiveness. The benefits identified in the interviews, which the case company has achieved through data analytics, are summarised in the table below (Table 5).

Table 5. Benefits identified in the interviews

Benefit	Description
Process improvement and work optimization	Streamlining procurement processes and reducing manual work.
Correction of errors and misunderstandings	Minimizing errors and misunderstandings by using accurate data in procurement decisions.
Improvement of procurement quality	Ensuring higher-quality procurement by utilizing data-driven insights to evaluate suppliers and purchases.
Enhanced monitoring	Improving supplier performance tracking, order fulfillment monitoring, and risk assessment.
Support for decision-making	Providing a factual basis for procurement decisions, reducing reliance on intuition and increasing confidence.
Improved negotiation position	Strengthening procurement's ability to negotiate better prices, terms, and supplier agreements.
Efficiency in quality measurement	Using data to measure supplier quality and ensure compliance with quality standards.
Cost savings	Reducing procurement costs through optimized purchasing strategies, better supplier management, and volume-based discounts.

4.5 Organizational culture

Organizational culture and employee attitudes play a key role in whether new ways of working can be internalized into existing processes. Two main factors typically emerge in this context: top management support and employee resistance to change. In addition to these phenomena, it is crucial that the organization fosters a "learning by doing" culture, where mistakes are allowed. This encourages employees to experiment and innovate. Based on the interviews, there has been a significant shift in the case company's thinking toward data analytics, but some challenges remain. In the case company, the organizational culture has changed, and as a result, analytics is now valued and actively utilized.

The cultural shift is evident, for example, in the transition from intuitive decision-making to more data-driven decision-making. According to the interviews, this change has been driven by the company's owners and top management team. While the case company has grown based on experience and intuitive decision-making, the top management has recognized the potential benefits of data. This perfectly illustrates the role of dynamic capabilities in the case company. However, the organization did not remain in the sensing phase; instead, the leadership team has actively sought to move the company toward the seizing and transforming phases. This is why the top management has made deliberate decisions that have promoted data-driven decision-making throughout the organization. The case company has now clearly transitioned into the transforming phase, where it continuously strives to advance in the field of analytics. In practice, the transforming phase involves organizations adopting new innovations, actively reshaping their organizational culture, and investing in the development of new operational methods. The interviews revealed that managers have been encouraged to embrace a “data-driven leadership” culture, leading them to set an example for their subordinates. As a result, analytics has gained increasing importance even within the case company’s procurement organization. In terms of dynamic capabilities, the beginning of the transforming phase in the case organization is evident in the integration of analytics and data into decision-making processes.

Although there has been a cultural shift in the case company toward analytics and data, the transformation is not yet complete. The interviews showed that some old ways of thinking still influence practices, which slows down the broader use of analytics. This is partly seen as resistance to change and a mindset that new technologies are unnecessary.

"We don't have any software other than Excel, we won't be going to the coding level in the future." – Interviewee A

4.6 Employees’ analytics capabilities

In addition to technology and procurement processes, employees need analytical capabilities to use and develop data analytics to meet future needs. The interviews strongly highlighted that data analytics will continue to be utilized in procurement, and the importance of data will increase significantly. According to the interviewees, procurement organization employees will need three skills in the future: technological skills, analytical thinking, and soft skills.

Technological and IT skills are important for all employees, regardless of the organization, because with digitalization, most tasks are handled through various systems. The interviews particularly emphasized the importance of knowledge in ERP systems and analytical tools, such as Microsoft Excel, which procurement employees must be proficient in. However, it is not enough to just use these tools, according to the interviewees, employees are expected to have better skills in presenting data visually.

"Essential information from Excel and presentation suggestions in a presentable format." – Interviewee A

According to the interviewees, the importance of analytical thinking will increase in the future, which is why procurement employees must be able to understand and utilize data in various business decisions. The rapid development of technologies requires companies to continuously adapt, and for this, procurement employees need ongoing learning.

"Yes, I believe in it, because the more it becomes part of everyday life and as we learn more about it, it's constantly changing. So, we need training for that." – Interviewee B

4.7 Developing data analytics in procurement

In recent years, the case company has emphasized the importance of data, which has been reflected in the increased use of analytics and the introduction of a new mindset within the organization. Managers have been specifically trained in data-driven leadership to help them understand how to leverage data in their daily work. Although the impact of data analytics has grown in the case company, it is still in its "infancy." During the adoption of data analytics, the case company has gone through all phases of dynamic capabilities. Although the development of technological solutions is slow, the significant cultural shift and investments in analytics indicate that the company has initiated a permanent transition toward a data-driven operating model. Numerous areas for improvement exist within the procurement organization, as highlighted by the interviewees. Opportunities for development include technology, processes, skills, and strategic practices. According to the interviewees, data analytics will play a significant role in the case company's procurement function in the future, making it essential to continuously evaluate and address development ideas.

"A significant role, absolutely. The decision has been made, and we've seen the benefits of using it, so we will continue to use it and emphasize its importance." – Interviewee B

The first area for development is improving the current systems, as highlighted by the interviewees. The ERP system could be made more user-friendly, and additional reporting tools could be implemented. As noted earlier, developing the case company's ERP system is a slow process, which makes improvements challenging with the current resources. Interviewee B mentioned considering the possibility of adding a separate analytics tool alongside the ERP system, which could bypass the slow development of the ERP system.

"I've sometimes toyed with the idea of whether it's possible to add a dedicated procurement and inventory tool alongside the ERP system." – Interviewee B

This could be a potential solution to the issues related to the ERP system's limitations and inadequate analytics capabilities, especially considering that the case company's marketing department already has a similar type of application in use. A separate tool could include various reporting templates and procurement-relevant metrics. These would collect real-time data from the ERP system, allowing managers to view the most up-to-date situation. A standalone analytics tool could, for example, provide a visual dashboard for inventory turnover and ABC analysis. This would enable the case company's procurement organization to reduce time-consuming manual work in Excel and improve the efficiency of its workforce.

Technology could also be developed by automating processes and implementing AI-based tools. The interviews revealed that, in the future, buyers could automatically receive alerts for necessary products, for example. In the long term, automation could be applied to operational procurement, such as for simpler spare parts orders.

“Purchasing will not change, unless through automation” – Interviewee B

For broader automation, the adoption of AI would also be necessary, as the products ordered in the case company's procurement vary greatly. Currently, buyers spend a significant amount of time searching for the required products, which takes time away from tasks that contribute to the company's development. Implementing AI could greatly enhance the efficiency of the case company's procurement process, and the interviewees share this perspective.

"The opportunities provided by AI, such as efficiency and speed" – Interviewee A

Artificial intelligence could be used in many different ways in the future, but decision-making should not be outsourced to it. According to interviewee B, the risk is that people will start to outsource decision-making to artificial intelligence more widely. This is one of the key risks if artificial intelligence were to be used more widely in the business world.

In the case of the case company, there is also room for improvement in processes and data quality. As was already clear earlier, procurement outside the processes is taking place, which weakens the reliability of analytics. Compared to technological development targets, it is easier to correct existing processes. In the case company's situation, it would be important to require everyone to act in accordance with the agreed processes, which would help to correct data quality problems. The ERP system should correct situations where there is no trace of procurement. In order to correct these shortcomings, management must actively promote the issue within the organization. With the support of management, resistance to change among personnel could be reduced and processes could be made to work.

A company may have advanced technology and high-quality processes, but it is essential that their users know how to use them correctly. The case company has organized numerous training courses for managers, but interviews revealed that not everything necessary has been taught. For example, people have not been trained at all in the enterprise resource planning system, which increases the variability of skill levels in the organization. For example, training days could be organized once a year for employees and managers using the ERP system, ensuring that the personnel have the necessary IT and analytical skills. In addition, separate groups, such as the purchasing organization, could have their own training regarding data analytics. The training days should also address skills that will be needed in the future, such as using artificial intelligence. Joint training could ensure that all personnel understand how artificial intelligence can be used in their own work and how one's own decision-making should not be outsourced to it.

Strategic development targets can be found in strengthening data-based decision-making. Both employees in the procurement organization and employees in other departments should be emphasized how data analytics supports everyone's work towards the company's goals. Emphasizing management by data could increase staff acceptance of data analytics. At a strategic level, the case company could create a clear analytics strategy for the organization, which would set goals and metrics for analytics at both the company and department levels. This would create a future-oriented direction.

The last development idea for improving the use of data analytics in the case company is to improve cooperation with other departments. The purchasing organization should cooperate more widely with other departments, for example by sharing information about inventory turnover. This way, other departments would know more precisely which products are in stock. Increasing cooperation would have a positive impact on the use of analytics and would concretize the new way of thinking.

As we have learned, the case company has several areas for improvement that, if enhanced, would enable the procurement organization to utilize data analytics more effectively and comprehensively. Figure 7 outlines how these identified areas for improvement should be addressed to successfully transition to a permanent data-driven operating model.

Figure 7. Steps for developing data analytics in the case company

In the first phase, the case company should increase training sessions, which have already been conducted for some employees. These training sessions should be expanded to cover the entire workforce, teaching them how to use the company's ERP system. As previously mentioned, separate training sessions should be organized for different organizational units when necessary, such as procurement-specific analytics training for the procurement organization.

In the second phase, since training has been conducted, employees can be expected to meet certain requirements. At this stage, it is essential to ensure that employees follow the agreed-upon processes. This guarantees, for example, the quality and availability of data, which are critical for analytics. These two development phases are relatively easy to implement with minimal resources but are crucial to complete before proceeding to the next stages. The development of data analytics could stall before fully integrating the new operating model if employees do not know how to use the systems or do not adhere to the established processes.

The third phase requires broader resources, as it involves upgrading the ERP system. Currently, system development is slow, and implementing change proposals takes a long time. Therefore, a more extensive update to the ERP system is needed. However, even with minimal resources, significant improvements in data analytics utilization in procurement could be achieved. As mentioned earlier, interview discussions included considerations about adding a separate analytics tool alongside the ERP system. This would likely be the first update in the third phase.

In the fourth phase, the company should turn its focus to advanced technologies. In analytics and more broadly within the case company, AI-based applications could be adopted. At this stage, simpler functions should also be considered for automation, especially after the ERP system has been updated in the previous phase. For example, automating stock replenishments and spare part orders in warehouses could be achieved with minor changes to the ERP system.

In the final phase, the data-driven operating model becomes fully embedded in the case company’s procurement organization, with processes such as purchase order automation in place. Predictive modelling tools would be adopted in analytics, enabling more accurate demand forecasting. By following these phases, the case company could take its use of analytics to the next level, significantly impacting the procurement organization’s operations. When considering these development suggestions, it is important to understand that completing these five phases will take several years. Therefore, it is crucial for the case company to begin addressing the identified issues now to avoid falling behind in development. Otherwise, there is a risk of losing competitiveness to rivals and jeopardizing the investments that have already been made.

5 Discussion and conclusions

In this section, a discussion is held based on the research questions and sub-questions. Through this discussion, conclusions are drawn. Finally, we evaluate the limitations of the study and consider suggestions for future research.

5.1 Discussions

The aim of this thesis was to fill the identified research gap and provide concrete answers to how data analytics could be utilized and developed in procurement. Next, we will examine the connection between the empirical results of the study and the theoretical background. The main research question of this thesis was:

How can data analytics be developed in purchasing and supply management?

Data analytics can be developed by investing in both current and new technologies. The primary goal for organizations should be to ensure that existing systems and processes operate flawlessly. This will ensure high data quality and easy accessibility for the procurement organization. Simply improving systems or analytics tools alone will not advance purchasing and procurement operations. Employees with analytics skills are also required. By training the staff, it is ensured that the entire organization understands the importance of data and can analyze raw data. According to researchers, in the future, organizations must focus on developing artificial intelligence, machine learning, and robotic process automation (Altundag & Wynn 2024; Arunachalam et al. 2018). With advanced technologies, analytics would become more reliable, and by automating processes, cost savings could be achieved. However, developing data analytics within organizations is challenging if the organizational culture does not support data-driven management and decision-making. Therefore, it is critical to ensure that when developing data analytics, efforts are made to embed a data-driven operating model within the organization. This means that data analytics should also be developed within procurement organizations at the cultural and attitudinal levels. The results indicate that data analytics can be improved across all different areas, but its development should consider the specific circumstances of the organization. In the case company, based on our analysis, data analytics could and should be developed across all key areas—technology, processes, organizational culture, and personnel.

In addition to the main research question, the thesis included sub-research questions that expanded the understanding of the study's topic.

How can data analytics be utilized in purchasing and supply management?

By analyzing data, companies can identify potential cost-saving areas and more comprehensively evaluate suppliers. Through data analytics, organizations can perform tasks such as ABC analysis, supplier scoring, or forecasting future needs. Reactive analytics helps identify past mistakes, from which the procurement organization can learn and avoid similar errors in the future. On the other hand, proactive analytics aims to better understand future needs, allowing procurement to optimize inventory levels. The results indicate that data analytics can be utilized at all levels: operational, tactical, and strategic. At the operational level, analytics could be used, for example, in tracking orders and deliveries. Furthermore, thanks to advanced technologies, simpler operational tasks could be automated, freeing up buyers' time for other critical tasks. At the tactical level, analytics could be applied in supplier management, where supplier performance could be monitored. In addition, data analytics could be leveraged in negotiations, which fall under tactical procurement. In organizations, it is generally emphasized that data analytics is a tool for strategic decision-making. In practice, this is reflected in the design of procurement strategies and processes and in risk management.

Why is data analytics utilized in procurement?

The importance of data analytics has increased in recent years with the advent of new technologies, which has led to a growing interest in data within organizations. The adoption of data analytics in organizations is typically driven by the concept of data-driven decision making and improving competitiveness. As competition intensifies, many organizations are seeking new ways to leverage dynamic capabilities, which data analytics represents. According to the results, one of the key reasons for utilizing data analytics in procurement is to enhance business operations. According to researchers, there is pressure to streamline procurement processes, which is why new technologies, such as data analytics, are being sought (Flechsig et al. 2022). In addition, the results highlighted aspects such as cost savings, procurement decisions based on facts rather than intuition, and increased negotiation power.

How do analytical capabilities and data analytics benefit purchasing and supply management?

According to researchers, the key benefits are cost savings (Handfield et al. 2019), process optimization (Karttunen et al. 2023), and improved decision-making (Bienhaus & Haddud 2018). The procurement organization of the case company has noticed significant benefits since the company began using data analytics. Data analytics can help optimize procurement and improve the efficiency of procurement employees. Through analytics, tracking and reporting can be improved. More detailed monitoring allows for the correction of errors and misunderstandings, which reduces the likelihood of procurement risks. With analytical skills, it is possible to derive insights from data that provide a solid foundation for decision making. Based on the interviews, data analytics is a key tool in strategic decision-making. With data, an organization can achieve cost savings, as analytics enable fact-based contract negotiations. The results indicate that employees' analytical skills and the use of data analytics in procurement provide numerous benefits to the entire company. These benefits enable companies to enhance their competitiveness relative to their rivals, potentially leading to a long-term competitive advantage.

What kinds of barriers exist to utilizing data analytics in procurement?

There are numerous obstacles and challenges to the adoption and utilization of data analytics. According to the results, the main ones relate to technology, personnel, and data. According to Flechsig et al. (2022), the level of IT infrastructure, such as ERP systems, can, in the worst case, prevent the implementation of data analytics. On the other hand, with digitalization, companies have invested in IT infrastructure, so this is unlikely to affect the utilization of analytics in organizations. Even if the ERP system is of high quality, its slow development can still be an issue. According to researchers, data-related problems are one of the most significant barriers to developing analytics, as, for example, poor data quality diminishes the reliability of data-driven decision-making (Arunachalam et al. 2018; Jain et al. 2024). Based on the interviews, it can be concluded that data-related challenges are indeed a key problem affecting the use of data analytics in procurement. Poor data quality not only prevents accurate analysis but can also lead to incorrect conclusions, which may have catastrophic consequences for the business. Another barrier could be employees' poor IT skills or varying skill levels among the staff. According to researchers, this could be due to a lack of training (Perçin 2023). The development of data analytics in organizations may also face resistance to change, which can paralyze the development of analytics processes. The results indicate that barriers and challenges can be found in processes, employees, technology, and data. It is important to understand that when integrating new practices or systems into existing ones, companies will almost always encounter obstacles and challenges. However, most of these can be overcome.

5.2 Conclusions

The goal of this research was to find solutions for how data analytics could be developed in purchasing and procurement. The amount of data has increased exponentially in recent decades, and many organizations have begun to leverage it. Handling raw data requires organizations to invest in analytics tools and the analytics capabilities of their staff. Data analytics functions as a dynamic capability within companies because it allows a company to react more effectively to changing conditions. The increased use of analytics has led to its growing implementation in procurement organizations within companies.

The adoption of data analytics in procurement organizations is justified by the benefits it creates. With data, organizations can base decision-making on facts instead of intuition. In addition, analytics can optimize company procurement and streamline procurement processes, saving employees' time. Data analytics enables the creation of more accurate reports, which can increase companies' negotiating power with suppliers. Developing procurement through data improves the organization's competitiveness because the likelihood of errors decreases, and the forecasting of future needs improves.

The adoption and development of data analytics in procurement may face challenges that slow down or, in the worst case, prevent the utilization of analytics in procurement organizations. The biggest barriers are related to insufficient or outdated technologies and systems. Additionally, weak analytics skills among employees pose problems, as raw data cannot be analyzed, or the conclusions drawn from analyses are incorrect. In some organizations, challenges may also arise from a lack of IT skills if employees are not trained or if there is resistance to change. Today, the vast amount of data itself creates problems, as it is necessary to sift through a sea of data to find the required information. In the case company, challenges have also arisen from the quality of data, which affects the accuracy of analysis results.

The case company's procurement organization can improve the use of data analytics in terms of technology, skills, and processes. By training employees, the quality of IT and analytical skills within the organization would be ensured. In addition, it is important for the case company to get its procurement processes functioning effectively so that data quality is not compromised. Regarding technologies, the case organization should consider improving current systems, although it does not have the authority to make changes to the ERP system. Data analytics should be developed using new technologies, such as artificial intelligence and machine learning. Moreover, the case organization should consider automating simpler procurement processes, which would significantly enhance the organization's efficiency. During the adoption of data analytics, the case organization has fully gone through the phases of dynamic capabilities: sensing, seizing, and transforming. The case company has entered the transforming phase and is moving toward a permanent analytical operating model, where data is at the core of both business operations and planning.

5.3 Limitations and suggestions for future research

When interpreting the results of the study, a number of limitations must be considered. This research was conducted as a case study, so the results cannot be generalized. The sample size may weaken the reliability of the study. In addition to the interviews, secondary sources were used, which helped improve the reliability regarding the sample size. The interviewees held managerial positions in the procurement department, and operational procurement employees were not included in the interviews. A limitation of the study lies in the interviewees. The results cannot be directly generalized to other departments within the case company because the procurement function has its own processes, and the study aimed to provide solutions specifically for the procurement organization.

To obtain generalizable results, it would be important to conduct a broader study focusing on service business companies, examining the use and development of data analytics from the procurement perspective. In addition, the rapid development of advanced technologies creates new topics for further research, such as the role of artificial intelligence and machine learning in the development of procurement analytics.

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Appendix 1. Interview questions

Background:

1. Who are you? What is your position in the organization? / Kuka olet? Mikä on roolisi organisaatiossa?

2. What are your main responsibilities? / Mitkä ovat pääasialliset vastuusi/tehtäväsi?

3. What is the organization's general attitude towards data analytics? / Millainen on organisaation yleinen suhtautuminen data-analytiikkaan?

Data analytics:

4. Do you use data analytics in your work? / Käytätkö työssäsi data-analytiikkaa?

5. Is the use regular or project-specific? / Onko käyttö säännöllistä vai projektikohtaista?

6. Do you use data analytics more reactively or proactively (anticipating future needs? / Käytätkö data-analytiikkaa enemmän reaktiivisesti vai proaktiivisesti (ennakoiden tulevia tarpeita)?

7. What kind of tools do you use in data analytics? / Millaisia työkaluja käytät data-analytiikassa?

8. Where do you collect data from, and what kind of data do you collect for data analytics purposes? / Mistä keräät dataa, ja millaista dataa keräät data-analytiikkaa varten?

Motivations behind utilization of Data Analytics in Procurement:

9. Do you generally view data analytics as a relevant tool in your work? / Näetkö data-analytiikan yleisesti hyödyllisenä työkaluna työssäsi?

10. How much do you use analytical procedures in your work? / Kuinka paljon käytät analytiikkaa työssäsi?

11. Is decision-making in the company generally based on data or intuition? / Perustuuko yrityksessä päätöksenteko yleisesti dataan vai intuitioon?

12. Does data analytics optimize your work and make it more efficient? / Tehostaako ja optimoiko data-analytiikka työtäsi?

13. Has the quality of procurement improved with the help of data analytics? / Onko hankintatoimen laatu parantunut data-analytiikan avulla?

14. How does data analytics add value to procurement processes? / Miten data-analytiikka tuo lisäarvoa hankintatoimen prosesseihin?

15. What are the overall benefits? / Mitkä ovat yleisimmät hyödyt?

Challenges/Barriers:

16. How would you describe the main challenges/barriers related to data analytics? / Miten kuvailisit data-analytiikkaan liittyviä keskeisiä haasteita/esteitä?

17. Do you feel that a lack of technology or skills impacts the adoption of analytics? / Koetko, että teknologian tai osaamisen puute vaikuttaa analytiikan käyttöönottoon/hyödyntämiseen?

18. Have data quality or data availability been obstacles to the development of analytics? / Onko datan laatu tai datan saatavuus estäneet analytiikan hyödyntämistä?

19. Is there top management support for the utilization of analytics? / Onko johdon tuki data-analytiikan hyödyntämiselle hankintatoimessa?

20. Has the use of data analytics encountered any resistance to change at any point? / Onko data-analytiikan käyttö kohdannut missään vaiheessa muutosvastarintaa?

Future:

21. What kind of role will data analytics have in procurement within your company in the future? / Millainen rooli data-analytiikalla tulee olemaan hankintatoimessa yrityksessänne tulevaisuudessa?

22. How do you think data analytics could be developed in your company? / Miten data-analytiikkaa voitaisiin kehittää yrityksessä?

23. How will new technologies shape or impact your work in procurement? / Miten uudet teknologiat tulevat vaikuttamaan työhösi hankintatoimessa?

24. How do you believe artificial intelligence, machine learning, or other advanced technologies will impact procurement data analytics? / Miten uskot tekoälyn, koneoppimisen tai muiden kehittyneiden teknologioiden vaikuttavan hankinnan data-analytiikkaan?

25. Do you believe that, in the coming years, employees and managers in procurement organizations will need more analytical capabilities in their daily work? / Uskotko, että tulevina vuosina hankintaorganisaatioiden työntekijät ja esimiehet tarvitsevat enemmän analyyttisiä kykyjä päivittäisessä työssään?

26. What skills and resources do you think will be needed in the future to leverage analytics? And what about on a more general level? / Millaisia taitoja ja resursseja koet tarvittavan tulevaisuudessa analytiikan hyödyntämiseksi? Entä yleisemmällä tasolla hankintatoimessa?