Ella Koivisto

AI-DRIVEN SUPPLIER PERFORMANCE MANAGEMENT

Natural Language Processing applications

Master of Science Thesis
Faculty of Management and Business
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October 2025

ABSTRACT

Ella Koivisto: AI-driven Supplier Performance Management ─ Natural Language Processing applications
Master of Science Thesis
Tampere University
Master's Degree Program in Industrial Engineering and Management
October 2025

The need for more integrated supply chains and buyer-supplier relationships has been increasing, due to accelerating competition and changing customer, buyer, and supplier needs. To achieve positive outcomes, including value creation and profitability in the supplier network, the buying organisation must provide means for comprehensive Supplier Performance Management. For performance management and measurement to be effective and proactive, buying organisations must incorporate the use of qualitative measures into their measurement process. To access these, various qualitative data sources and technologies that enable their use must be considered. This study aimed to address this issue and the currently limited understanding of it. The goal was to identify how Natural Language Processing could be applied in Supplier Performance Management, from the perspective of the buying organisation. The aim was to gain a deeper understanding of current challenges in Supplier Performance Management, identify current information needs, possible qualitative data sources, and assess the potential of Natural Language Processing to enhance Supplier Performance Management through proactive measurement.

Based on the existing literature, supplier performance is typically measured through quantitative indicators. Current performance frameworks typically focus on reactive methods, often neglecting proactive and qualitative measures. However, proactive indicators based on qualitative data are significant and should be taken into consideration in supplier performance evaluation. Qualitative performance measures create opportunities for artificial intelligence technologies, particularly in Natural Language Processing. While Natural Language Processing is utilised in subfields, in Supplier Performance Management, it has not yet been widely recognised. Therefore, to address the existing research gap and develop comprehensive performance measurement, qualitative data and use cases for Natural Language Processing are recognised.

To meet the research objectives, a qualitative study of two semi-structured interview rounds on Finnish large manufacturing organisations was conducted. The first interviews created an understanding of current information needs regarding suppliers. Through the second interview round, categorisations of current challenges, qualitative data sources, proactive supplier measures, and potential use cases of Natural Language Processing were distinguished. The results were compared to the existing literature to provide answers to all the research questions and create a framework regarding the potential of Natural Language Processing in identified use cases. Based on the research, use cases exist in proactive supplier performance categories: quality, delivery performance, operations and processes, organisation and business, connections, sustainability, and innovation.

The results of this study show that the supplier information needs, qualitative data sources, existing challenges, and Natural Language Processing use cases can be categorised based on proactive supplier performance categories. The key findings highlight the significance of qualitative data in proactive measurement and the potential of Natural Language Processing in this context. This thesis contributes to the existing literature by broadening the perspective on a capable supplier, while successfully connecting it to qualitative data and Natural Language Processing in a manner that has not yet been explored in existing research. In addition, this thesis encourages future research to further examine the subjects in practice, shifting Supplier Performance Management overall towards more digitalised environments.

Keywords: Artificial Intelligence, Natural Language Processing, Large Language Models, Supply Chain Management, Supply Chain, Supplier Performance, Supplier Performance Management

TIIVISTELMÄ

Ella Koivisto: Toimittajien suorituskyvyn hallinta tekoälyavusteisesti — Luonnollisen kielen prosessoinnin sovelluskohteet
Diplomityö
Tampereen yliopisto
Tuotantotalouden diplomi-insinöörin tutkinto-ohjelma
Lokakuu 2025

Jatkuvasti kiihtyvä kilpailu yritysten välillä, sekä asiakkaiden, valmistajien ja toimittajien muuttuvat tarpeet ovat kasvattaneet yhtenäisten toimitusketjujen sekä toimittajasuhteiden merkitystä. Positiivisia tuloksia, kuten arvonluontia tai kannattavuutta, voidaan toimitusketjuissa saavuttaa, kun valmistava yritys monipuolisesti hallitsee toimittajien suorituskykyä. Suorituskyvyn hallinta ja mittaaminen on tehokasta ja proaktiivista, kun valmistajat huomioivat myös kvalitatiivisia mittareita. Jotta näitä voidaan hyödyntää, tulee valmistajien selvittää kvalitatiiviset datalähteet, sekä teknologiat, jotka mahdollistavat datan käytön. Tämän tutkimuksen tavoitteena oli tunnistaa, kuinka luonnollisen kielen prosessointia voidaan hyödyntää toimittajien suorituskyvyn hallinnassa erityisesti valmistajien näkökulmasta. Tavoitteena oli saada lisää ymmärrystä nykyisistä toimittajien suorituskyvyn hallinnan haasteista, tunnistaa nykyisiä toimittajiin liittyviä tietotarpeita ja näihin sopivia kvalitatiivisia tietolähteitä sekä arvioida luonnollisen kielen prosessoinnin potentiaalia toimittajien suorituskyvyn hallinnan parantamisessa proaktiivisten suorituskykymittareiden kautta.

Aiemman kirjallisuuden mukaan toimittajien suorituskykyä on tyypillisesti mitattu kvantitatiivisten mittareiden avulla. Nykyiset suorituskykymittaristot keskittyvät usein reaktiivisiin menetelmiin ja jättävät proaktiiviset ja kvalitatiiviset mittarit huomiotta. Kuitenkin proaktiiviset suorituskykymittarit ovat merkittäviä ja ne tulisi huomioida toimittajien suorituskyvyn hallinnassa. Kvalitatiiviset suorituskykymittarit luovat mahdollisuuksia liittyen tekoälyn sekä etenkin luonnollisen kielen prosessoinnin hyödyntämiseen. Luonnollisen kielen prosessointia on aiemmissa tutkimuksissa tarkasteltu yrityksen eri toiminnoissa, mutta toimittajien suorituskyvyn hallinnassa sitä ei ole vielä kuitenkaan tunnistettu. Jotta tunnistettuun tutkimustarpeeseen voidaan vastata ja kokonaisvaltaista toimittajien suorituskyvyn mittausta kehittää, tulee kvalitatiivinen data ja luonnollisen kielen prosessoinnin käyttökohteet tunnistaa.

Jotta tutkimuksen tavoitteet voitiin saavuttaa, toteutettiin diplomityössä kvalitatiivinen tutkimus puolistrukturoitujen haastattelujen kautta. Haastatteluiden kohteena olivat suuret suomalaiset valmistavan teollisuuden yritykset. Ensimmäisen haastattelukierroksen avulla selvitettiin tietotarpeita, joita toimittajiin tällä hetkellä liittyy. Toisen haastattelukierroksen aineistojen perusteella rakennettiin kategorisoinnit nykyisistä haasteista, kvalitatiivisista data lähteistä, proaktiivisista suorituskykymittareista sekä potentiaalisista luonnollisen kielen prosessoinnin käyttökohteista toimittajien suorituskyvyn hallinnassa. Haastattelujen tuloksia verrattiin kirjallisuuteen, jotta kaikkiin tutkimuskysymyksiin voitiin onnistuneesti vastata ja luonnollisen kielen prosessoinnin käyttökohteet voitiin tunnistaa. Tutkimuksen perusteella käyttökohteet jakautuvat tunnistettuihin suorituskykykategorioihin, joita ovat laatu, toimituskyky, toimenpiteet ja prosessit, organisaation rakenne ja liiketoiminta, suhteet, kestävyys sekä innovaatiot.

Tämän tutkimuksen tulokset osoittavat, että toimittajiin liittyvät tietotarpeet, kvalitatiiviset datalähteet, nykyiset haasteet ja luonnollisen kielen prosessoinnin käyttökohteet voidaan kaikki kategorisoida toimittajien proaktiivisten kyvykkyyskategorioiden avulla. Keskeiset tulokset korostavat kvalitatiivisen datan tärkeyttä suorituskyvyn hallinnassa sekä näyttävät potentiaalin, joka luonnollisen kielen prosessoinnilla on tässä kontekstissa. Tämä diplomityö laajentaa nykyistä ymmärrystä toimittajien suorituskyvystä ja luo uutta tietoa liittyen kvalitatiiviseen dataan sekä luonnollisen kielen prosessoinnin hyödyntämiseen toimittajien suorituskyvyn hallinnassa. Lisäksi tämä diplomityö kannustaa tutkimaan aihetta lisää konkreettisella tasolla, jotta toimittajien suorituskyvyn hallintaa voidaan ohjata kohti digitaalisempia toimia ja ympäristöä.

Avainsanat: Tekoäly, Luonnollisen kielen prosessointi, Kielimallit, Toimitusketjujen hallinta, Toimitusketju, Toimittajien suorituskyky, Toimittajien suorituskyvyn hallinta

USE OF AI IN THESIS

I have utilised AI tools in my thesis:

- ☐ No
- ☒ Yes

The AI tools utilised in my thesis, and their purposes are described below:

Names and versions of AI tools: Microsoft Copilot (GPT-4), Scopus AI, Grammarly (14.1122.0)

Purpose of using AI tools:

Microsoft Copilot was used for translating words and finding synonyms. Grammarly was used to improve grammar and phrases of which the researcher was unsure. The changes that AI has done to the text, is add, remove or change commas or articles, or certain phraseologies. Scopus AI was used to assist the writer in searching of research articles in the context. In addition, the interviewee transcripts were translated with the assist of Microsoft Copilot.

Sections where AI tools were used:

Throughout the whole thesis, AI was used to find synonyms, translate words, and improve grammar. Scopus AI was utilised in literature research. Results can contain quotes that have been translated by AI.

I acknowledge that I am fully responsible for the entire content of my thesis, including the parts generated by AI, and accept accountability for any violations of ethical standards in publications.

PREFACE

At the end of the year 2024, a friend of mine said to me that they had seen an interesting project, which, in their words, *summed me up as an academic*. Now, after seven months of active working and approximately 600 cups of coffee, I have successfully finished my thesis for the said project. That basically sums me up as an academic, and as a person too.

At the beginning of 2025, I received the great opportunity to write my thesis as part of the OSCG group at Tampere University. Considering my studies, I couldn’t be more thankful, as the AI-SIM project combines both my academic and personal interests. Writing my thesis for the project was the perfect finalisation to my highly rewarding — and partly complicated and confusing — studies in university. So, although my studies have not completely been *easy peasy lemon squeezy (*more like *difficult difficult lemon difficult)*, I can finally say that I made it.

That said, I am extremely grateful to my examiners, Doctoral Researcher Elviira Saarelma and Professor Aki Jääskeläinen, for giving me this opportunity, supporting, and guiding me throughout the whole writing process and the sometimes-stupid questions and panic-moments. In addition, I want to thank all the other AI-SIM project colleagues and the professionals who participated in the interviews conducted for this research for their valuable input. Furthermore, I want to acknowledge my colleagues at IEM, who made the writing process and the late nights at the office actually fun, through the endless laughs, coffee breaks, and mutual suffering. It has been a privilege to work alongside each and every one of you!

Five years of studies, and a memorable phase of my life, are coming to an end, and even if I still don’t have an answer to the question of what I want to be when I grow up, I am happy. Although the future is a foreign land, I am excited to take the next steps and see where the tide carries me next!

In Tampere 03.10.2025

With kind regards,

Ella Koivisto

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LIST OF SYMBOLS AND ABBREVIATIONS

AI	Artificial Intelligence
AI-SIM	AI-Driven Renewal of Business and Supplier Information Management
API	Application Programming Interface
BDA	Big Data Analytics
COA	Certificate of Analysis
CRM	Customer Relationship Management
DEI	Diversity, Equity, and Inclusion
DL	Deep Learning
ERP	Enterprise Resource Planning
ESG	Environmental, Social and Governance
GPT	General-purpose technology
IoT	Internet of Things
IS	Information Systems
I4.0	Industry 4.0
LM	Language Model
LLM	Large Language Model
ML	Machine Learning
NLG	Natural Language Generation
NLU	Natural Language Understanding
NLP	Natural Language Processing
OSCG	Operations and Supply Chain Group
P4.0	Procurement 4.0
PSM	Purchasing and Supply Management
RFI	Request for Information
SBTi	Science Based Targets initiative
SCM	Supply Chain Management
SPM	Supplier Performance Management
TF-IDF	Frequency-inverse document frequency

1. INTRODUCTION

The first chapter introduces the subject of the master's thesis to the reader. This chapter begins with a brief background to the subject and explains the motivation behind the research. The introduction then proceeds to the objectives and research questions, along with the scope of the thesis. In the final section of this chapter, the structure of the research is introduced.

1.1 Background and motivation

As competition between organisations accelerates, pressure regarding supply chains has been increasing. Supply chains, consisting of companies that participate in the various stages of the product manufacturing process, are considered one of the core functions of the procurement process. (Nyamah et al., 2023; Weele, 2018) More integrated relationships in supply chains can create advantages, such as more open information exchange and efficient conflict-resolution mechanisms, for all participants (Monczka et al., 2009). Investments in supplier relationships can be utilised to strategically create a higher awareness of the supply network's opportunities, performance, and capabilities, as well as to create value and gain a preferred status in the network (Kähkönen et al., 2015; Patrucco & Kähkönen, 2021).

Regarding supply chains, Purchasing and Supply Management provides the means for expected performance and changing needs of buyers, suppliers and customers, while correlating positively with organisations' performance and profitability (Loureiro et al., 2021), and working as an important part of the organisations' whole strategy (Gunasekaran et al., 2004; Jääskeläinen et al., 2023; Zimmermann & Foerstl, 2014). Purchasing and Supply Management consists of different managerial practices (Zimmermann & Foerstl, 2014), from which this research emphasises the supplier-facing, or supplier-oriented practices, and even further the Supplier Performance Management.

Supplier performance measurement is a significant part of Supplier Performance Management. It consists of parameters, such as quality, delivery, costs, and sustainability (Maestrini et al., 2018) that traditionally are measured with an emphasis on quantitative and operational methods (Cho et al., 2012; Cousins et al., 2008). Although more proactive methods, including qualitative measurement, such as social capital assessment, have been raised to be beneficial for the buyer-supplier relationship (Jääskeläinen et al., 2023). Nevertheless, performance metrics enabling proactive measurement based on qualitative data are still lacking or not used efficiently, partly because they are difficult to express or measure numerically (Beamon, 1999). Therefore, it can be interpreted that the understanding and knowledge regarding qualitative data and its exploitation in performance management are insufficient.

Because of emerging technology use, Supplier Performance management as it used to be, might not work anymore. This is why it must go through a transformation to stay efficient (Gattorna & Ellis, 2020). This change has highlighted the different supplier data and information needs and their evolution in supply chains. Said information, however, traditionally refers to quantitative data, which is utilised in reactive management, leaving a lot of the potential of qualitative data and proactive management unutilised. However, research considering the use of textual data analysis has recently been getting attention (e.g. Balan et al., 2024; Janjua et al., 2023).

As information and information sharing are important parts of the relationships in a supply chain, in response, organisations have started to invest in information technologies. (Baah et al., 2022; Kumar & Pugazhendhi, 2012) Greater digital transformations, as for example digital business models (Kohtamäki et al., 2019) and Industry 4.0, have revolutionised organisations, Supply Chain Management, and Supplier Performance Management with different technologies (Althabatah et al., 2023), and this direction of development is only accelerating.

One of said technologies is artificial intelligence (AI), which despite its potential, is still in the early stages of use in procurement processes and supply chains (Guida et al., 2023). AI is considered to be one of the components of Industry 4.0 (Ustundag & Cevikcan, 2017), and it has been a technology trend for a long time (Ma et al., 2024). AI can be defined as algorithms, software, and computer architectures that are capable of communicating with humans and can imitate human capabilities (Toorajipour et al., 2021). Research considering the use of AI in business and related processes has been a subject of interest for researchers too (Loureiro et al., 2021). However, the research has been limited to marketing, manufacturing, and sales (Guida et al., 2023; Loureiro et al., 2021). Regarding different AI applications, most of them are utilised in the operative production context, which can be explained through the practicality and operationality of the measures (Toorajipour et al., 2021). Furthermore, the production practices might be seen as repetitive and of a routine nature, which has opened opportunities for automation and AI technologies. The current research has mainly focused on forecasting, such as planning and supplier selection (Toorajipour et al., 2021), and more operational tasks, such as risk management (Guida et al., 2023), primarily through quantitative data analysis, making it still insubstantial.

According to Büyüközkan & Göçer (2018), supply chains carry a large amount of information, part of which exists in an unstructured or qualitative form, therefore remaining unutilised. A promising AI solution developed for qualitative data analysis is Natural Language Processing. Natural Language Processing consists of a collection of techniques, which, instead of binary language, understand and analyse written or spoken human language. (Garg et al., 2023) Although Natural Language Processing has gradually become more common in different fields in the business context, such as in marketing (Mariani et al., 2023), it has not yet been thoroughly researched in the SPM context. Typical Natural Language Processing techniques are, for example, spoken and written language understanding, sentiment analysis, language generation, information retrieval, and question answering (Deng & Liu, 2018). In the business context, Natural Language Processing is utilised for example for report summarising, meeting translations, sentiment analysis on social media, or extracting interesting keywords from documents (Balan et al., 2024; Chae, 2015; Jha et al., 2022; Treiblmaier & Mair, 2021). Similar to Deng & Liu (2018), in this master's thesis, human language will be referenced to as natural language.

In Supplier Performance Management, as AI applications are still developing, Natural Language Processing remains significantly unresearched. This can be explained through the previously mentioned issue of lacking methods of collecting and even recognising the existence of qualitative data, such as textual data. However, there is a great amount of textual, unstructured data hidden in supply chains that carries a lot of potential (Treiblmaier & Mair, 2021; Wu, 2024) regarding insights about suppliers and their performance in a proactive manner. That said, in this research, proactive measurement is seen to consist of the utilisation of unstructured data, and therefore, qualitative measures in this thesis go hand in hand with proactive measures. As traditional supplier performance frameworks often can be seen to lack in incorporating proactive and qualitative measurements, this thesis aims to challenge the existing reliance on quantitative measures and contribute by researching the potential of unstructured data.

Performance signals can be, for example, interpreted from meetings, organisation managers' phone calls, or conversations (Wu, 2024), or through text documents such as annual reports (Jegadeesh & Wu, 2013) or news articles (Tetlock et al., 2008). As qualitative data has become more generalised, Supplier Performance Management too must shift from using only numerical indicators in assessing suppliers, into creating a more comprehensive and data-rich way of managing the performance, with the combination of both quantitative and qualitative methods.

As stated, a significant research gap combining Supplier Performance Management, proactive measurement, and qualitative data analysis is identified. Based on existing literature, it appears that the subjects can be improved by researching and developing ways to understand, analyse, and manipulate natural language. Therefore, the purpose of this master's thesis is to broaden the previous research about Natural Language Processing and deepen the understanding about its applications in the supplier performance context regarding proactive measurement.

This master's thesis is connected to Tampere University's faculty of Management and Business and the AI-Driven Renewal of Business and Supplier Information Management (AI-SIM) project. The AI-SIM project is conducted by the Operations and Supply Chain Group (OSCG). The project includes deep collaboration between Tampere University, Turku University, and three partaking organisations. The project network also consists of other organisations and European universities. The AI-SIM project research AI-based solutions for supplier relationships, management, and networks, with an emphasis on Natural Language Processing methods. The goal of the project is to investigate AI and discover ways to transform supplier networks and management through it. This thesis takes part approximately in the middle of the project, and thus the objective of the thesis is to deepen the knowledge and research of using Natural Language Processing in supplier performance management. The project is funded by Business Finland.

1.2 Research objectives and research questions

The key objective of this thesis is to understand the potential of Natural Language Processing in Supplier Performance Management. This master's thesis aims to determine current information and improvement needs in proactive measurement, as part of Supplier Performance Management, and determine how Natural Language Processing can be utilised in them. The objective is to explore the recognised use cases of Natural Language Processing in Purchasing and Supply Management, with an emphasis on supplier assessment, and develop a use case framework based on them. The research moves from theoretical analysis to empirical analysis with the aim to conduct analysis on the current situation of the subject, identify the research gap and then contribute to it comprehensively.

The defined objectives are aimed to be achieved through chosen research questions. The main research question focuses on improving Supplier Performance Management through proactive measurement. The sub-questions are formed to support the main research question and divide the subject into smaller, more explicit components. The main research question is finally answered through said components.

This research addresses the following main research question:

> **RQ1:** How Supplier Performance Management could be improved through proactive measurement?

In addition to the main research question, the following sub-questions are addressed:

> **RQ2:** What are the current information related needs in Supplier Performance Management?
>
> **RQ3:** What kind of supplier performance factors could support proactive measurement?
>
> **RQ4:** How Natural Language Processing could be utilised to support proactive Supplier Performance Measurement and Management?

By answering these research questions, the master's thesis develops contributions to both practical and academic purposes. This master's thesis aims to contribute to exploit Natural Language Processing in Supplier Performance Management to increase efficiency and improve the processes of Supply Chain Management, which supports the practical and managerial contributions. From academic point of view, this research aims to examine the existing needs of improvement and information in Supplier Performance Management through studying the characteristics and requirements of supply chains in the chosen scope. Additionally, this thesis aims to contribute to the recognised research gap by combining supplier capability, qualitative data and Natural Language Processing in a way that has not yet gotten significant recognition in operations management research.

1.3 Research scope

The scope of this master's thesis conducts the previously stated research questions and determines the perspective from which the subject is researched. The thesis focuses on the buying organisation's point of view but recognises the importance of the whole buyer-supplier relationship. Supply chains are examined as large networks of multiple suppliers.

This thesis concentrates on strategic procurement, therefore considering long-term Supplier Relationship Management. The subject is approached through the perspective of Purchasing and Supply Management, and the management practices are briefly introduced as a background to Supplier Performance Management. The scope is then narrowed by only focusing on supplier capabilities as part of supplier assessment, since for example risks have already been researched more thoroughly. While this research briefly introduces AI and it’s methods in the supply chain context, the scope is narrowed down to Natural Language Processing and it’s possibilities regarding Supplier Performance Management and proactive supplier performance measurement. The research focuses on large Finnish organisations operating in the manufacturing industry. This decision was made to narrow the research scope and to get a deeper understanding of significant organisations and their processes.

1.4 Research process and structure

The research process for this thesis started in March 2025. The first steps included the background analysis, the selection of the thesis topic and then doing background research about said topic. After the researcher familiarised with the subject, a more thorough background analysis was started to determine the research gap, research problems and finally the research questions. In parallel, the researcher started the analysis process of existing interview transcripts and cooperatively coded the interviews with another researcher of the project. Soon after that, the planning process of new interviews started, and the research progressed to the empirical analysis. Since the research subject is quite new, it is important to use the empirical analysis as a guide for what kind of possibilities this research can achieve. The research process steps, and the researched phenomena are illustrated as a flowchart in figure 1.

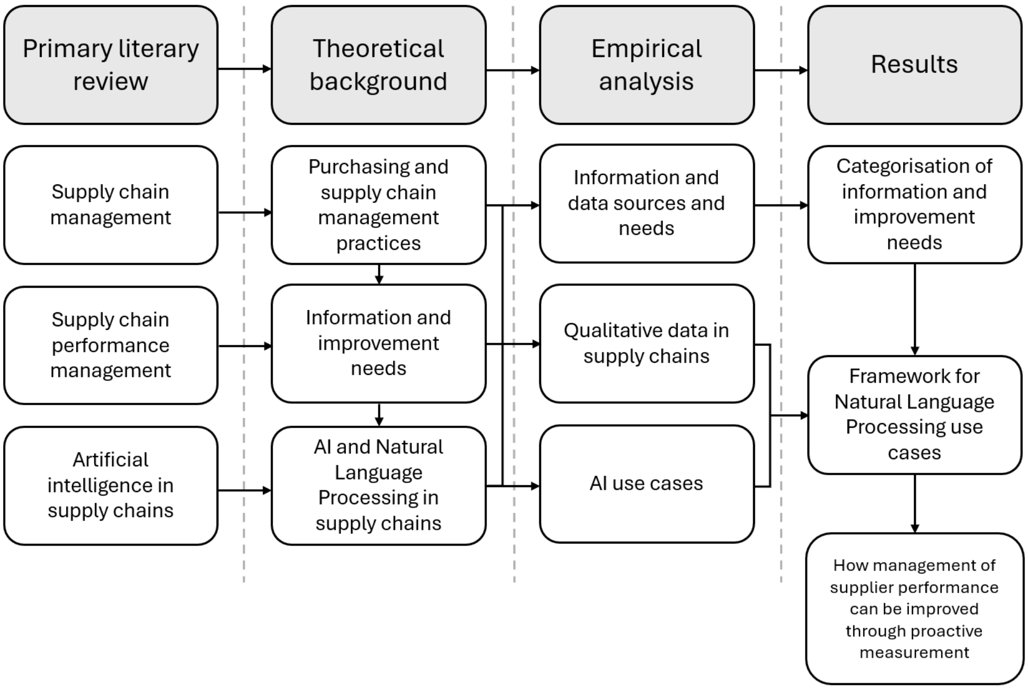

Figure 1. The research process flowchart.

After the literature review and the empirical analysis, the research process moved on to connecting the findings gained from the mentioned parts. The synthesis is bringing together the identified needs and details both from the literature and the empirical data, and builds results based on them. After writing the results and conclusions, the thesis was finalised and iteratively checked to ensure the expected quality. The finalisation of the thesis was done during September 2025.

This research contains theoretical and empirical parts which both are at the end extended to one entirety and then concluded to the research's context. Through the theoretical analysis, the purpose has been to get a deeper understanding about current Supplier Performance Management techniques and to research the current potential of Natural Language Processing in the context. The empirical part's purpose has been to provide a more concrete dimension to the subject. Overview of the master's thesis' structure is introduced on table 1.

Table 1. The structure of the master's thesis.

Chapter	Subject	Content
1.	Introduction	Research background and motivation Research objectives and research questions Research scope and structure
2.	Theoretical background	What is Purchasing and Supply Management and what practices does it include? How is supplier performance measured and managed, and what kind of performance aspects exist? What are the current information needs in supply chains? How artificial intelligence is utilised in supply chain context? What is Natural Language Processing and how can it be utilised?
3.	Research methodology	Used methodology, research process and methods
4.	Results	Analysis of the interview results
5.	Discussion	The combined research findings from both the theoretical and empirical analysis
6.	Conclusions	Achievements and contributions

The following chapter focuses on the theoretical background of the research based on the previously introduced research scope. The chapter introduces the procurement process and the basics of Supply Chain Management. Because of digitalisation and data usage, the information needs have evolved and therefore the chapter also focuses on what qualitative information needs exist in proactive supplier measurement and how they have changed through for example generalised data and technology use. Supplier performance, key performance factors and performance management are introduced with the emphasis on qualitative data. Lastly, the theoretical background introduces the artificial intelligence methods used in supply chain context and Supplier Performance Management before focusing on Natural Language Processing and its applications.

In the third chapter, the research methodology and chosen research strategies are introduced. The chapter begins with the introduction of the research philosophies and methodologies, built from both empirical and theoretical research, and then proceeds to show the data collection and analysis methods used in the research. The chapter also explains the research process, beginning with the theoretical research and continuing into the empirical research process which consists of data collection and analysis process of two interview research materials.

The results of the research and the analysis are described in the fourth chapter. The chapter is based on the empirical methods introduced in the second chapter. In the fifth chapter, the empirical findings are combined with the context of the literature review. The fifth chapter provides answers to the research questions and together with chapter four give a clear synthesis to all the research results.

The sixth and final chapter of the thesis focuses on final conclusions and contributions of the research while mirroring the research questions stated in the beginning of the introduction. This chapter states the academic and managerial contributions of this master's thesis. The quality of the research is assessed critically through reliability and validity, and finally, the chapter introduces the limits of the research and gives insights into future research possibilities.

2. THEORETICAL BACKGROUND

In this chapter, purchasing and supply management and supplier performance are researched through literature. The general nature of the subjects is then combined into digitalisation, technology, data and AI. The theoretical background also introduces the improvement and information needs recognised in the Supplier Performance Management. Natural Language Processing is discussed as an AI technique, before moving on to introducing the existing use cases in related fields.

2.1 Purchasing and Supply Management

The organisation's act and process of acquiring and sourcing services and goods is called procurement (Ambekar et al., 2021). Brandmeier & Rupp (2010) introduce how supplier management is one of the core functions of procurement, and how especially the integration of suppliers correlates strongly with procurement success. As the procurement process manages inbound and outbound resource flow of the organisation, inside supplier management, it has a function called Purchasing and Supply Management (PSM) (Bag et al., 2020). Whereas Supply Chain Management (SCM) consists of a broader perspective of supply chains, PSM focuses only on external resources that are needed to maintain the processes of a company. Thus, PSM is the primary function that is responsible for sourcing items from suppliers and defining the supply strategy and supplier network design. (Patrucco & Kähkönen, 2021; Weele, 2018)

Monczka et al. (2009) define purchasing as a functional activity that performs operations related to delivering maximum value through supply chain activities in the procurement process. Weele (2018) defines purchasing as the management of a company's external resources in a way that all the necessary processes of their primary and support activities are maintained. Supply management however, refers to the strategic approach of achieving organisations mission through planning, and acquiring organisations future and current needs by managing its supply base, therefore making it a broader concept than purchasing (Monczka et al., 2009). Weele (2018) defines supply as a term related to buying, as it includes inspection and receiving of incoming materials, gained through purchasing. In this thesis, purchasing and sourcing are discussed as synonyms and from now on, referred to only as purchasing. Purchasing and Supply Management is also referred to as a unified term, without separating the terms from each other.

2.1.1 Purchasing and Supply Management process

While PSM's earliest mentions go back to the 1830s (Weele & Raaij, 2014), PSM as a phenomenon has become significant in the 1980s through the first published frameworks with a focus in cost savings and cost efficiency. As the demand for new products increased, companies started to develop ways to be more flexible in product development processes. Therefore, the primary idea of PSM functions was tied to profitability enhancement and the procurement of cheaper materials through supplier capabilities. (Foerstl et al., 2017; Monczka et al., 2009) As the emphasis first was in downstream and aftermarket services, it later widened to handle the upstream processes too (Monczka et al., 2009), eventually transforming the role of PSM from linear to cross-functional, affecting the whole organisation and procurement process. The transformation into more co-operative buyer-supplier-relationships has integrated PSM into all functions in organisations, including logistics, marketing, and information systems (IS) (Monczka et al., 2009). Currently, PSM is considered to be one of procurements primary and most important activity (Bag et al. 2020).

Bals et al. (2019) introduce PSM processes that are divided into two different aspects: Source-to-contract and Purchase-to-pay, from which the first is more strategic and the latter a more operational process. The mentioned processes can be combined into the procurement process, as Source-to-contract fits the sourcing, and Purchase-to-pay fits the supply part. Source-to-contract -process consists of organisation's spend and demand analysis, demand management, negotiation and implementation, which are mostly done in collaboration with the supplier, while Purchase-to-pay consists of requisition and approval of the supplier, ordering of resources, order confirmation and payment of said goods which are done more independently in the buyer organisation (Bals et al., 2019; Weele, 2018) Nevertheless, the processes still operate simultaneously.

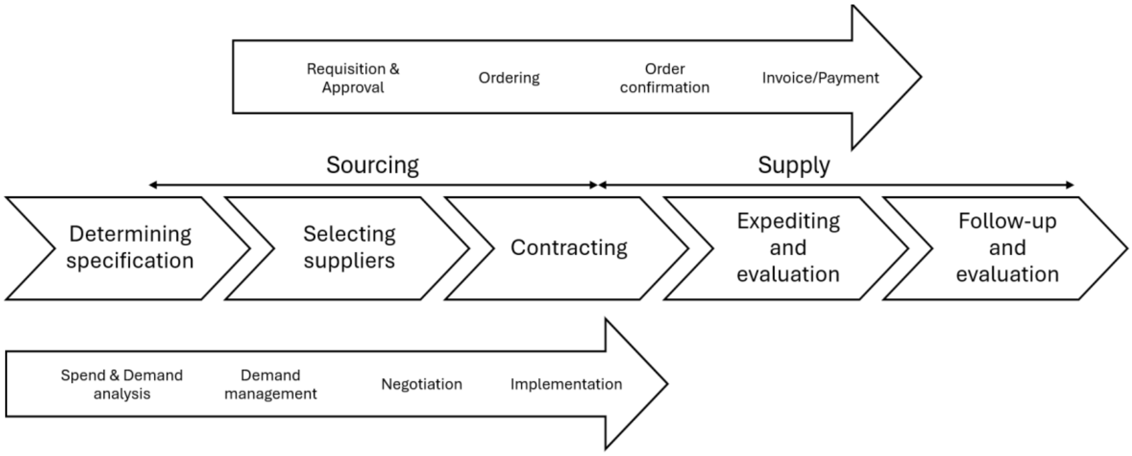

Figure 2. PSM processes in procurement process (based on Bals et al. 2019; Osmonbekov & Johnston, 2018; Weele & Raaij 2014; Weele 2018).

The Charity Institute of Purchasing & Supply currently define PSM as the business management function that ensures all the steps seen in the procurement process model (Pereira et al., 2020). PSM therefore combines the organisation's strategy into the procurement process, and it controls, organises and deploys the assets, resources and processes to ensure the effectiveness and safety of the buyer-supplier relationship and creates competitive advantage through it (Pereira et al., 2020).

2.1.2 Purchasing and Supply Management practices

To maintain PSM's strategic role and competence, organisations must develop capabilities, knowledge, and experience regarding PSM within the professionals (Weele & Raaij, 2014). On the other hand, the mentioned also connect PSM deeper into the procurement process and increase the level of strategic alignment with the organisation's suppliers (Patrucco & Kähkönen, 2021). According to Weele (2018), the main responsibilities of PSM managers are risk management, innovation and continuous improvement, cost control, and operational excellence. Monczka et al. (2009), on the other hand, introduce specification reviewing, contacting suppliers, evaluating and selecting suppliers, and purchasing contract awarding. The responsibilities introduced by Monczka et al. (2009) resemble the procurement and PSM process steps introduced previously in figure 3. Based on this, it can be interpreted that the responsibility of PSM professionals is to support the procurement function and processes, all while working as the closest communicator between the buyer and the supplier.

The responsibilities can be achieved through PSM practices. Zimmermann and Foerstl (2014) categorise PSM practices into supplier-facing practices and internal PSM practices. As the terms indicate, the internal practices consider the organisation's strategy and the internal functionalities that align with it, while the supplier-facing practices focus more on the supply chain actors, their relationship, and functions. (Jääskeläinen & Heikkilä, 2019; Zimmermann & Foerstl, 2014) Internal practices are further divided into four subcategories, which are vertically aligned PSM practices, cross-functional integration practices, within PSM practices, and enabling PSM practices.

Vertically aligned PSM practices focus on aligning the PSM function with the organisation's strategy, including, for instance, centralisation and decentralisation (Weele & Raaij, 2014). Cross-functional integration practices, on the other hand, focus on integrating the PSM with other organisational functions, such as marketing or R&D. Within practices are defined as ones that happen inside the PSM function, such as order processing and preparations within the function, while enabling PSM practices include those that can be used to develop PSM further, such as technology acquisition or employee skill practices. (Jääskeläinen & Heikkilä, 2019; Zimmermann & Foerstl, 2014) In addition, Truong et al. (2017) introduce three different practices that can be connected to the internal PSM practices. These practices include process control and improvement, top management support, and customer focus (Truong et al., 2017), from which the first can be put under enabling PSM practices, and the latter two can be put under cross-functional practices. Additionally, lean and efficiency management can be categorised as enabling PSM practices (Weele & Raaij, 2014).

Supplier-facing practices are divided into relational and nonrelational PSM practices. Relational PSM practices require mutual effort from all the participants in the supply chain, which are the buying organisations and suppliers, therefore including, for example, supplier involvement and risk management (Weele & Raaij, 2014). Nonrelational practices require resources and effort primarily from the buying organisation. (Jääskeläinen & Heikkilä, 2019; Zimmermann & Foerstl, 2014) Relational practices include for example knowledge sharing, supplier involvement, Supplier Relationship Management, communication, or joint product management. Nonrelational practices, on the other, hand include supply base reduction, supplier selection and evaluation, supplier development and Supplier Performance Management. (Jääskeläinen & Heikkilä, 2019; Terpend et al., 2008; Zimmermann & Foerstl, 2014) Carter et al. (2017) complement the mentioned by introducing interorganisational practices that include supplier development for sustainability and electronic data interchange with suppliers. Truong et al. (2017) also introduce supplier management as one of the PSM practices, and this can be connected into supplier-facing practices. A classification containing all the introduced categories and practices can be seen in table 2.

Table 2. PSM practices.

Category	Subcategory	Definition	Practices	Sources
Internal PSM practices	Vertically aligned PSM practices	Practices that align PSM with the whole strategy of an organisation.	Strategy alignment, centralisation and decentralisation	Weele & Raaij, (2014); Zimmermann & Foerstl, (2014)
	Cross-functional PSM integration practices	Practices that connect PSM into other organisational functions.	Marketing, R&D, top management support, customer focus	Jääskeläinen & Heikkilä, (2019); Truong et al. (2017); Zimmermann & Foerstl, (2014)
	Within PSM practices	Practices done within the PSM function.	Preparations, order processing	Jääskeläinen & Heikkilä, (2019); Zimmermann & Foerstl, 2014
	Enabling PSM practices	Practices done to develop PSM.	Improving employee skills, technology acquisition, process control and improvement, lean and efficiency management	Truong et al. (2017); Weele & Raaij, (2014); Zimmermann & Foerstl, (2014)
Supplier-facing PSM practices	Relational PSM practices	Practices that require effort from both the buying organisation and suppliers.	Knowledge sharing, supplier involvement, Supplier Relationship Management, communication, joint product management, risk management	Jääskeläinen & Heikkilä, (2019); Terpend et al. (2008); Weele & Raaij, (2014); Zimmermann & Foerstl, (2014)
	Nonrelational PSM practices	Practices that require effort mainly from the buying organisation.	Supply base reduction, supplier selection and evaluation, supplier development, Supplier Performance Management	Carter et al. (2017); Jääskeläinen & Heikkilä, (2019); Terpend et al. (2008); Zimmermann & Foerstl, (2014)

The focus on this thesis is moved towards nonrelational PSM practices, and especially Supplier Performance Management. This practice is further introduced in subchapter 2.3.3, after supplier performance and capability as a subject are introduced.

2.2 Supplier performance

PSM must analyse and assess the performance of suppliers in order to fulfil the short and long-term needs and goals of the buying organisation (Gunasekaran et al., 2004). According to Sherwin et al. (2025) and Sarkar & Mohapatra (2006), the overall performance of supply chains is affected by the performance of the different individuals existing within it, thus partly relying on suppliers' performance. Supplier performance is connected to Supplier Performance Management (SPM), which is part of the nonrelational PSM practices introduced earlier.

The performance of an organisation, team, or individual is something that is generally measured to distinguish their efficiency or capability. Supplier performance as a term can be interpreted slightly differently based on the point of view, and for example the information context.

2.2.1 Definition of supplier performance

The measurement of organisational performance considers how well the organisational objectives are fulfilled (Drago et al., 2022). In the supply chain context, a supplier's performance refers to how well the supplier organisation can respond to the buying organisation's needs, through the competitional advantages that they have enabled by using resources that they possess (Maestrini et al., 2018). Drago et al. (2022) broaden the view by introducing alignment with dynamic environmental changes.

Capability can be seen to be related to performance, as it refers to a firm's capacity of undertaking a particular productive activity in a way that distinguishes it from its competitors (Rashidirad et al., 2015), which compared to the definition of performance, leans more into the supplier organisation's ability to take on to the given requests coming from the buying organisation. On the other hand, Leiringer & Zhang (2021) define organisational capabilities as the entirety of resources, routines, skills, behaviours, and competences that an organisation must possess to achieve competitive advantages, growth or performance, or to operate functions reliably to move towards a determined goal. However, for example, Ruuska et al. (2013) support a view in which different supplier capabilities form potential value and advantages to the buying organisation. Other research follows the same idea, introducing supplier capabilities as potential factors influencing the supplier performance and further affecting the whole supply chain performance and buying organisation's success (e.g. Dey et al., 2015; Gunasekaran et al., 2004; Jääskeläinen, 2018).

Another term related to supplier performance is supplier competence. This can be seen coming from a similar idea as capability, since aspects of competitiveness that work as the organisation's competitive advantages, such as resources, capabilities, or dynamic capabilities (Rashidirad et al., 2015), contribute positively to the supplier performance. Chikán & Gelei (2010) introduce organisational competence as the firm's ability to create efforts to profit and survive in constantly changing external and internal environments. In this view, competitiveness is created through operational competencies and value dimensions that must be fulfilled. For this thesis, a comprehensive term of performance is created through the combination of the introduced terms. Table 3 brings together the definitions and the term of performance used in this thesis.

Table 3. Terms related to supplier performance.

Term	Definition	Sources
Performance	Organisation’s ability to answer to a defined set of needs and goals	Maestrini et al. (2018)
Capability	Organisation’s capacity and resources to in a competitive and well performed manner to take on productivity activities raised by the buying organisation	Chikán & Gelei, (2010); Rashidirad et al. (2015); Ruuska et al. (2013)
Competence	Raised from the supplier’s desire of success, the organisational ability to create efforts to survive in a changing environment	Chikán & Gelei, (2010); Rashidirad et al. (2015); Ruuska et al. (2013)
Performance in this thesis	Supplier’s capability and ability to through different tangible and intangible resources, referred to as capabilities, answer to the defined needs (for example short and long-term goals) of the buying organisation, in order to enable and fulfil the buying organisations short- and long-term goals.	

Leiringer & Zhang (2021) argue that the current understanding of performance is based on capabilities enhancing it, although the connections between the terms are not clearly explained. According to Laaksonen & Peltoniemi (2018), an organisation’s capabilities are the working force that creates changes in its performance. This contradicts the common belief that capabilities are the functions that explain performance as it is. However, Sarkar & Mohapatra (2006) introduce how performance represents effects seen on short-term, and capability, on the other hand, indicates to the longer-term effects.

Drago et al. (2022) review the relationship between capabilities and performance, connecting it to strategic behaviour within the organisation. Strategic behaviour is seen as an enabler that allows the organisational capabilities to affect the performance positively. Rashidirad et al. (2015), on the other hand, introduce strategic resources as the basis of an organisation’s capabilities, which iteratively work together, are maintained, upgraded, and fulfilled in order to move towards the chosen goals (Rashidirad et al., 2015).

2.2.2 Performance aspects

Performance factor is defined as a certain metric that indicates the efficiency of an action done by an organisation (Neely et al., 1995). A supplier can be capable in different ways, based on the point of view from which it is inspected. Therefore, a supplier might be seen as capable in certain aspects, such as logistics, technology, or processes, while being less capable in others.

Ruuska et al. (2013) divide supplier capabilities into three capability bases: technical and operational, relational, and developmental capabilities. Operational and technical capabilities focus more on the processes and products of manufacturing, while relational capabilities focus on organisational capabilities and relationships. Developmental capabilities consider those that might arise, for example, from the supplier’s ability to evolve and prosper. (Ruuska et al., 2013) The capability bases can be further divided into capability categories. Maestrini et al. (2021) introduce quality, delivery, innovation, and sustainability as categories of supplier performance that can be improved, for example, through performance measurement systems. Ruuska et al. (2013) complement this with technical, operational, and relational capabilities. In addition, Möller & Törrönen (2003) discuss organisational capabilities as a function that increases suppliers' performance and, for instance, value-creation potential.

Furthermore, key performance factors can be classified under the mentioned categories. The performance factors considered in this thesis are qualitative in nature, opposed to traditional measures that usually focus on financial and numerical data. The performance factors can be seen as aspects of the supplier organisation that help them develop performance in the mentioned capability categories. The framework containing the bases, categories and aspects can be seen in table 4.

Table 4. Categorisation of supplier performance aspects.

Capability base	Capability categories	Key performance aspects
Technical and operational capabilities [a]	Quality [a, c, d]	Compliance [d], Improvements [b, d, e], Data and reporting [d], Action systems [d]
	Operations and processes [a, b]	Certifications [b], Skills and knowledge [b], Productivity [d], IT infrastructure [b], Visibility and Traceability [b, d, h]
	Delivery performance [a, b, c, d]	Accuracy [b, d, e], Reliability [e], Incoterms [b, d], Regulatory requirements [d], Performance [b, d, e], Protocols [b]
	Technology/product [a, f]	Technology [g], Customisation [g], Durability [g]
Relational capabilities [a]	Organisation and business [a, b, d]	Agility [b], Adaptability [a, b], Financial stability and strength [d], Image [d], Past records [d]
	Connections [a, b]	IS integration [b], Networking and relationships [e], Reputation [b], Social exchange [b]
Developmental capabilities [a]	Innovation [a, b, c]	R&D achievements [b, e, f], Qualifications [b], Technology use [f, g], Innovation strategy [b, f]
	Environmental [c, d] sustainability	Waste management [d], Clean technologies [d], Eco-friendly materials [d], Pollution prevention [d], Carbon footprint [c, d]
	Social sustainability [c, d]	Ethical policy [d], Human rights [c, d], DEI [d], Safety [h], Employee welfare [h], Labour practices [h]
a: Ruuska et al. (2013) b: Möller & Törrönen, (2003) c: Maestrini et al. (2021) d: Dey et al. (2015)		e: Pressey et al. (2009) f: Iddris, (2016) g: Saunila et al. (2021) h: Kazançoglu et al. (2023)

Technical and operational capabilities include performance aspects related to quality, processes, delivery and technical details. Quality-related aspects are, for example, the supplier's readiness for improvements, if quality-related issues emerge (Gunasekaran et al., 2015). The other performance aspects in this capability base are connected to the actual production and delivery of the products and services, and consist of for example the supplier's certifications, productivity, and traceability, while also considering the supplier's IT infrastructure, delivery accuracy and performance, product technology and durability, and supplier compliance (Dey et al., 2015; Pressey et al., 2009; Şen et al., 2008).

Relational capabilities consider the supplier's organisational and relational capabilities, which are grounded in relationships and, for example, organisational culture and structures. The drivers or performance aspects in these categories include, for example, IS integration, organisational image, past records, networking and relationships (Dey et al., 2015; Ruuska et al., 2013), social exchange or social capital (Jääskeläinen et al., 2023). From the developmental capabilities, innovation, which can be divided into incremental and radical innovations, consider the supplier's ability to through these developments open up new business opportunities and solutions, thereby supporting the business of the buying organisation (Ruuska et al., 2013). The previously mentioned product category can also be considered in innovations, as it can be seen through for example R&D achievements, strategies or technology acquisition and use. (Möller & Törrönen, 2003; Pressey et al., 2009) Sustainability contains performance drivers regarding environmental or social factors and Diversity, equity, and inclusion (DEI), in the manufacturing process, products, and organisational culture (Dey et al., 2015; Kazançoglu et al., 2023)

The categorised aspects are the ones distinguished as interesting in regard to proactive measurement and natural language data sources. In other words, these performance aspects are the ones that are recognised to require qualitative data analysis. However, while factors such as quality, delivery, or reliability can be measured in quantitative methods (Şen et al. 2008), to effectively recognise a well-performing and capable supplier, qualitative methods are needed to support them. In addition, Hallikas et al. (2021) argue that measures based on qualitative factors are as significant as those based on quantitative factors, for example, in terms of prediction, thereby creating an existing link between qualitative data analysis and proactive measures.

2.2.3 Supplier Performance Management

Supplier Performance Management (SPM) is one of the PSM practices introduced earlier. As a research study, SPM emerged in the late 1980s (Thorpe & Beasley, 2004; Thorpe & Holloway, 2008), from where it has been undertaken in various management fields, including HR management, marketing, and operations management (Busi & Bititci, 2006). The overall significance of SPM has been increasing, thus creating a pleasant environment for supplier development and proactive PSM (Jääskeläinen et al., 2023).

SPM can be seen to include two strategic core practices: the evaluation and improvement of an organisation's suppliers' performance (Zhou, 2016). This combines the performance factors distinguished by the buyer into the capabilities of the suppliers.

A high-level categorisation of SPM can be made by distinguishing the different needs of measurement. The needs determine the objects of measurement, which can be either the whole supply chain or a single supplier. For example, Gunasekaran et al. (2004) and Aslam et al. (2018) focus on measuring the entire supply chain, while measurement of single suppliers is researched by, for example, Boukrouh et al. (2024) and Cavalcante et al. (2019). Another classification can be done through a framework that divides performance management into operational, tactical, and strategic levels, making operational performance focused on day-to-day measures while, for example, the strategic level focuses more on metrics that can be compared to industry norms, such as cost savings or quality (Gunasekaran et al., 2004).

The introduced categorisations are related to the root reasons of why measurement overall is done. Reasons behind SPM create a natural connection between SPM and the organisation's strategic goals in the short and long term and clarify the profound need for why measurement is done. Table 5 summarises the reasons motivating SPM and supplier measurement.

Table 5. Reasons for SPM.

Motivation	**Description**	**Source**
Continuous improvement	SPM is utilised to enhance the buying organisation's overall competitiveness and developmental capabilities through improvement strategies and innovations.	Cavalcante et al. (2019); Gunasekaran et al. (2004)
Financial effectiveness	Partnerships are utilised in order to increase financial performance through efficient cooperations, information sharing and lowered costs.	Gunasekaran et al. (2004)
Customer satisfaction	Competitiveness is increased through capabilities regarding dynamic and changing environments, to further create value and answer to the customers' needs.	Aslam et al. (2018); Gunasekaran et al. (2004)
Delivery flexibility	Utilising SPM to improve the buying organisation's production performance and order efficiency, regarding for instance accommodation to fluctuations in demand.	Cavalcante et al. (2019); Gunasekaran et al. (2004)
Operational performance	Through efficient supply chain structures, the buying organisation can make their internal operations more efficient and competitive.	Aslam et al. (2018)
Risk management	By understanding supplier performance and supply chains thoroughly, buying organisations can improve resilience and identify opportunities regarding improved sourcing.	Cavalcante et al. (2019)

As a concluding remark, evaluation is to be done based on the attributes of performance that the buying organisation sees as significant. Supplier evaluation is done through different methods, which, for example, are simpler weighted methods or more complicated methods including different techniques, such as neural networks (Sarkar & Mohapatra, 2006). In addition, evaluation methods, such as linear programming, multi-attribute rating techniques (Ho et al. 2010), and fuzzy set theory (Zhou, 2016) can be utilised. More traditional frames that support capability assessment are, for example, balanced scorecards and performance pyramids (Cousins et al., 2008).

Supplier evaluation needs might arise during new product development, new market or product line expansion, supply base reduction, or current suppliers insufficient performing, but also when changes in the supplier base are made, such as when a contract is ending or needs for buying certain goods emerge (Gallear et al., 2022; Monczka et al., 2009; Sarkar & Mohapatra, 2006). The emerging needs for evaluation create a process that moves from recognising the need for evaluation, into determining requirements, strategy, and sources and finally to the decision of supplier evaluation methods and measurement systems (Monczka et al., 2009). Supplier performance monitoring, on the other hand, includes possible ending of the supplier-buyer relationship and supplier identification (Doshi, 2019). This process however can be divided into the following active phases of supplier measurement: requirement for supplier evaluation, determining attributes of performance, and performance evaluation and monitoring (figure 3).

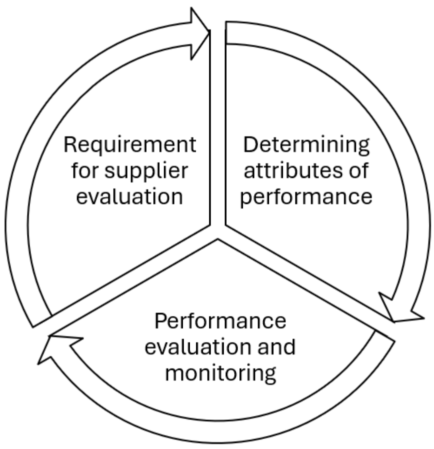

Figure 3. Supplier evaluating process (modified from Doshi 2019; Monczka 2009).

Buying organisations typically use a tailored performance measurement system that helps the buying organisation connect supplier capabilities to their expected needs and goals. Through the system, the buying organisation evaluates the capabilities and performance of the supplier, focusing on different performance factors from different categories. Neely et al. (1995) define a performance measurement system as a method of using a set of predetermined performance metrics to quantify the performance of actions, both in effectiveness and efficiency. Gunasekaran et al. (2004) complement this by stating that the measurement system should represent the organisation’s goals, while also reflecting a balance between quantitative and qualitative, as well as financial and non-financial aspects. An excellent performance measurement system’s characteristics should also include the monitoring of past performance while also planning for future performance, providing feedback fast, and be derived from the organisation’s strategy (Cocca & Alberti, 2010). Performance measurement itself can positively influence the competitiveness of networks and organisations, and enable new ways of organisational learning (Jääskeläinen, 2018), and therefore its operational continuity should be ensured. Maestrini et al. (2018) also indicate that there is a positive relationship between supplier performance measurement, measurement system adoption, and the supplier’s performance.

2.2.4 Challenges in Supplier Performance Management

While SPM has been introduced as a process that highly supports both the buying organisation and its suppliers, places of improvement exist. However, regarding the scope of the thesis, it is important to note that based on the existing literature, challenges related to qualitative data are not specifically emphasised. Table 6 presents currently recognised challenges in SPM. The challenges are categorised by the phase of supplier evaluation they exist in, and whether they relate to the buyer’s organisation or the technology and data. As seen from the table, challenges related to the buyer are seen in every phase, but especially in the first two phases. Challenges related to technology and data, on the other hand, surface more in the phase regarding the evaluation itself.

Table 6. SPM challenges in different phases of evaluation.

Phase of evaluation	Challenge type	Challenges	Sources
Requirement for supplier evaluation	Technology	System integration is inadequate	Howells, (2024)
	Buyer	SPM practices are inconsistent or lacking	Romule et al. (2020); Gunasekaran et al. (2004)
		Organisation's objectives are quantitative	Thorpe & Holloway, (2008)
		Difficulties regarding supply chain transparency and uncertainty exist	Burgess et al. (2024); Şahin & Topal, (2019)
Determining attributes of performance	Buyer	Performance factors are not aligned with the buying organisation's goals	Thorpe & Holloway, (2008); Cousins et al. (2008)
		Performance factors are not categorised or weighed	Gunasekaran et al. (2004)
		Only traditional performance factors are considered	Boukrouh et al. (2024); Zheng et al. (2022);
Performance evaluation and monitoring	Technology	The evaluation based on qualitative data is highly resource-consuming	Sarkar & Mohapatra, (2006)
		All capabilities do not exist in measurable form for utilisation	Thorpe & Holloway, (2008); Sarkar & Mohapatra, (2006); Schaltegger et al. (2015)
		Unstructured data exists in large amounts	Sarkar & Mohapatra, (2006)
	Buyer	Inefficient information sharing between buyer and the supplier	Modi & Mabert, (2007)

As introduced, the objects of assessment are typically quantitative, which makes the evaluation of intangible assets highly difficult. Thorpe & Holloway (2008) discuss that traditionally, in performance management, it is assumed that relevant data is either easily collected or already available for the organisation to use. This creates difficulties regarding qualitative data, for example, about suppliers' relational capabilities, since it can't be expected to exist in numerical form that the buying organisation possesses. Sarkar & Mohapatra (2006) argue that capability factors that are qualitative in nature present measurement problems. Beamon (1999) also indicates that qualitative measures are often hard to utilise in a meaningful way, compared to quantitative methods.

Boukrouh et al. (2024) also indicate that relying solely on quantitative data may lead managers to overlook profound perceptions created by, for example, more subjective methods, thus failing to gain a comprehensive understanding of the scope of performance. Zheng et al. (2022) add that supplier performance criteria might tend to include only essential indices, such as quality or delivery, but lack on, for example, factors related to sustainability.

In addition to the importance of recognising all significant performance aspects from both tangible and intangible assets, PSM must define performance factors and goals in a way that aligns with the buying organisation's goals. As the importance of strategic alignment was previously introduced, it must be implemented through multidimensional frameworks or models that concentrate on vital activities (Thorpe & Holloway, 2008). However, Romule et al. (2020) suggest that if the performance metrics are not consistent and too many performance systems exist simultaneously, the whole process might become complex and inefficient. The framework should also allow the managers to categorise performance metrics based on their weighted importance. It has been researched that creating effective SPM practices inside the buying organisation can create financial benefits for the participating organisations. (Gunasekaran et al., 2004) Combining the supplier capabilities and performance, and their measurement into risk management is also essential (Thorpe & Holloway, 2008; Ruuska et al., 2013), but as risk management is outside of the scope of this thesis, this aspect will not be discussed further.

Howells (2024) introduces the idea that another challenge is the siloed nature of data, software, and professionals within organisations. This indicates that integration of different IS, platforms and data sources is still inadequate. In addition, qualitative and unstructured data exist in large amounts, making the analysis process highly resource-consuming (Sarkar & Mohapatra, 2006). However, this is tied to the context, and differences do exist. For example, Schaltegger et al. (2015) introduce that certain sustainability-related information, such as labour conditions and ecosystem maintaining, are difficult to measure quantitatively. The difficulty of analysing unstructured data creates the possibility of acquiring AI technologies for use.

Enrique et al. (2022) introduce that supply chains have uncertainties that raise need for information and information sharing. Supply chain uncertainties can be divided into uncertainties related to upstream or downstream, of which upstream uncertainties are supplier-related (Enrique et al., 2022). Şahin & Topal (2019) support this view by highlighting various uncertainties related to supplier information and performance, including quality, flexibility, delivery, and sustainability. On the other hand, Burgess et al. (2024) introduce supply chain transparency as a difficulty and the primary motivator behind information needs in supply chains.

Modi & Mabert (2007) argue that supplier performance is positively affected by collaborative communication, indicating that the performance of the supplier cannot be ensured without efficient information sharing and IS between the organisations. Therefore, knowledge sharing is highlighted. Cousins et al. (2008) add that the buying organisation should create conditions that allow both the buyer and the supplier to develop the relationship through their contributions. Data and information needs must be recognised and addressed from the buying organisations' point of view.

2.2.5 Evolving needs of supplier information

As information technologies have advanced and the significance of supply chains and supplier relationships has risen, the information shared in supply chains has become critical (Kumar & Pugazhendhi, 2012). Baah et al. (2022) complement this by addressing that information sharing enables efficiency and effectiveness between operations regarding customer needs and market demands of participants in a supply chain. In addition, because of the constantly changing markets and the growing need for adaptability, firms must have information about their suppliers and the external environment. In addition, Hillard (2010) introduces an estimate indicating that 30-40 % of the value in organisations is tied up in information. Kumar & Pugazhendhi (2012) similarly suggest that, at least in some circumstances, information sharing in businesses can be highly beneficial. The increasing amount and significance of supplier data drives buyers towards more digital decision making, prompting the acquisition of new technologies, such as machine learning, relevant (Cavalcante et al., 2019)

Data refers to the various types of information collected from certain sources. In the supply chain context, data can be defined as a concept that includes information of different types, which is collected from various parts of the supply chain. In this thesis, data is defined to be raw information that has not yet been further processed into usable information or knowledge. Data is seen to be a driver of more efficient decision-making and better profitability in companies (Waller & Fawcett, 2013). This can be inferred from the insights provided by data, regarding, for example, market trends, customer patterns, or maintenance cycles (Wang et al., 2016).

The general process is that data is developed into information that can be utilised by managers. Howells (2024) defines information as something that derives processes and events, and it is the number of unique states of every output of the situation. Brinch (2018), on the other hand, considers information as something generated from the data, to be used to understand the original data. Relatedly, Hillard (2010) introduces a data development model, which is visualised in figure 4. This pyramid can also demonstrate the use of data in decision-making processes. All this data and information includes metadata, which can be defined as data about data, considering, for example, contextual information (Hillard, 2010). Hallikas et al. (2021) highlight that gaining knowledge from the original data and the digitalised processes in procurement and SPM is highly important.

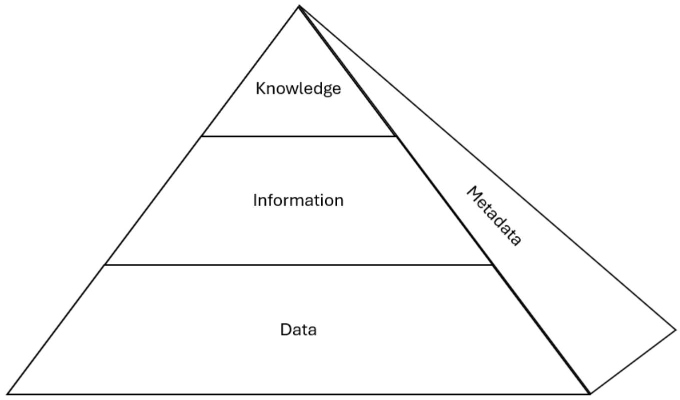

Figure 4. Development of data to knowledge (modified from Hillard 2010).

According to Brinch (2018), data can exist in different sources, which are, for example, sustainability data, internet data, market data, and financial data, from where they are collected and further utilised. Data types existing in the mentioned sources can be related to products and machines, sales, supply chain events, suppliers, or sustainability, and they are generally based on the types of structures and participants in the supply chain (Akhavan & Zvezdov, 2021; Brinch, 2018; Waller & Fawcett, 2013). Innovation data is also mentioned as essential, for example, in innovation projects (Patrucco et al., 2022). The categories can be seen to follow a similar classification regarding supplier capability bases, as introduced by Ruuska et al. (2018).

Types of information existing in SPM are connected to the data types. Kumar & Pugazhendhi (2012) introduce manufacturing-related information types, which are categorised as information related to the process, inventory, resources, orders, and planning. According to the information needs introduced by Kumar & Pugazhendhi (2012), most focus on quantitative demand or production data, such as costs, lead times, and order sizes. However, Burgess et al. (2024) introduce information needs with a more qualitative nature, such as environmental and social sustainability, quality, deliveries, operations, and suppliers as an organisation. Information related to the whole supply chain, as well as the deliveries, can be found in qualitative form too (Schaltegger et al., 2015; Seok & Nof, 2018). Additionally, information needs related to suppliers innovations, such as R&D projects, development of operations, and application efficiency of knowledge, exist in qualitative form (Jean et al., 2012; Patrucco et al., 2022).

Järvi & Munnukka (2009) categorise information sources into two categories: internal and external. Internal information is defined as information acquired through an organisation's internal sources, such as company reports and studies, personnel, databases, and intraorganisational sources (Craig & Allen, 2013; Järvi & Munnukka, 2009; Wu, 2024). External information can further be divided into supplier-provided information, which consists of suppliers' materials, analyses, and databases, and other external information, such as the internet, news, and other business associates (Craig & Allen, 2013; Deeter-Schmelz & Kennedy, 2004; Järvi & Munnukka, 2009). Although it must be noted that information sources are not tied to information types but rather exist in all categories. The information needs are however, connected to the data types and information sources (table 7).

Table 7. Classification of data types, information sources and generated information.

Capability base	Data types	Information source	Examples of information
Technical and Operational capabilities	Product and machine data [b]	Supplier's materials [d, e] Company reports [d, e] Databases [e] Others inside buyer's organisation [d, f, m]	Production methods [f] Performance and governance [f, a] Quality practices and quality certifications [f, h]
	Supply chain event data [a, b]	Industry reports and studies [d, e] Analyses [e] Consultants [e] Databases [e]	Supply chain process [f] Delivery information [f, a, h, g]
Relational capabilities	Supplier data [b]	Supplier's materials [d, e] Internet [d] Outside business associate [e, f] Company reports [d, e]	Supplier information [h, a] Supply chain structure [h, g, i] Compliance [h, i]
Developmental capabilities	Sustainability data [c, b] Innovation data [j]	Internet [d] Supplier's materials [d, e] News [e, d, l] Interpersonal sources [e, m] Intraorganisational sources [e, f]	Labour conditions and safety [h, i] Environmental safety [h, i] Legal and civil rights [h, i] CO2 impact and environmental impact [h, i] Product and technology enhancement [k] R&D projects [k, j] Knowledge application [k, j]
a: Waller & Fawcett, (2013) b: Brinch, (2018) c: Akhavan & Zvezdov, (2021) d: Deeter-Schmelz & Kennedy, (2004)		e: Järvi & Munnukka, (2009) f: Kumar & Pugazhendhi, (2012) g: Schaltegger et al. (2015) h: Seok & Nof, (2018)	i: Burgess et al. (2024) j: Patrucco et al. (2022) k: Jean et al. (2012) l: Handfield et al. (2019) m: Wu, (2024)

The information needs and capability aspects that the buying organisation appreciates can be seen to go hand in hand in the SPM process. Therefore, this connection highlights more profoundly the specific information needs that exist in the SPM process and in supplier evaluation.

2.3 Data in supply chains

In the context of Industry 4.0 (I4.0), procurement 4.0 (P4.0) has been simultaneously developing. P4.0 refers to data integration in supply chains and involvement of digitalisation (Bag et al., 2020). On the other hand, Sjödin et al. (2023) define P4.0 as an approach to procurement that, through digitalisation, aims to optimise supply chain agility, innovation and, efficiency.

The goal is to integrate manufacturing into data chains with the help of the internet and technologies. (Jahani et al., 2021) The growth in both diversity and amount of data has led organisations to use technologies, since the data sets are no longer manageable in traditional ways (Waller & Fawcett, 2013). The collected data is transformed into information through techniques such as predictive analysis or smart logistics systems (Büyüközkan & Göçer, 2018; Schoenherr & Speier-Pero, 2015). Data is utilised and handled through SCM data science, which Waller & Fawcett (2013) have introduced as the application of qualitative and quantitative methods, combined with theoretical SCM disciplines, with the aim to solve relevant issues and predict outcomes, while considering data quality and availability.

Based on its nature and format, data can be structured or unstructured. Structured data is organised in a specific format, making it well-defined and requiring less processing, which makes it easy to use in data analysis. Structured data can be classified into parameters and variables through the use of a database (Handfield et al., 2019), and it can, for example, exist in SQL tables (Howells, 2024). Unstructured data, however, does not exist in a predefined format, and it can include a wider array of information: images, emails, documents, or videos. Unstructured data generally contains textual data and is not based on numerals as structured data typically is. (Howells, 2024; Tetlock et al., 2008; Treiblmaier & Mair, 2021) Semi-structured data, on the other hand, falls between the two mentioned data types, containing aspects from both of them. Semi-structured data, for example, can be an HTML web page file that contains functions such as markers or tags, which can be helpful in data organising (Howells, 2024). In this thesis, unstructured data is connected to qualitative data, integrating the two terms into synonyms. This indicates that the data is considered to primarily include textual data and natural language.

2.3.1 Collection and analytics

Unstructured data can be collected from various sources. Internal data sources include the organisation's own databases or information gathered directly from suppliers. Qualitative data can be collected from written reports, contracts, or messages and emails between the buying organisation and the supplier (Handfield et al., 2019; Tetlock et al., 2008). External sources, on the other hand, include sources outside the supplier-buyer relationship. These can be websites or databases provided by externalised third parties, which can include government agencies or commercial data aggregators, or application programming interfaces (API) (Chen et al., 2015; Howells, 2024). Additionally, data collection can be conducted, for example, from social media, news feeds, and company reports (Handfield et al., 2019).

According to Howells (2024), to enable the full potential of data science, managers need to understand what happens in data processing and storage. Typical locations for data storage include databases, such as relational, graph or document databases, or data warehouses (Howells, 2024; Schoenherr & Speier-Pero, 2015). Cloud computing is also used as a solution. Cloud computing enables potentially unlimited virtual computing resources and extensible storage allowing data analysts to analyse the data without managing advanced computer infrastructure (Howells, 2024).

To successfully gain insights from the data, the next step is to process it. According to Howells (2024), data processing generally includes data preparation, transformation, and analysis. For this, organisations typically use technologies, such as forecasting techniques, data mining, or analytical mathematical modelling (Waller & Fawcett, 2013). Handfield et al. (2019) support this by introducing statistics, graphical visualisation tools, simulation, and mathematical algorithms. AI techniques can be applied to automate and improve the processes. However, Howells (2024) emphasises that the data analysis model must be integrated effortlessly into the broader IS architecture, including databases, APIs, systems, and user interfaces.

According to Handfield et al. (2019), data analytics typically operate on structured data, highlighting a gap in addressing unstructured data. In SCM, automatic analysis has only been infrequently used on unstructured data (Treiblmaier & Mair, 2021). This means that unstructured data needs to be better integrated into use, by potentially acquiring new techniques. Although qualitative information is difficult to analyse and visualise, ways to quantify it exist (Jegadeesh & Wu, 2013), opening up possibilities in unstructured data analysis.

2.3.2 Predictive analytics and proactive methods

It is essential to understand the datasets and systematically examine them to identify characteristics, patterns, and trends. By doing this, the data can be further developed for use in visualisations and models. (Howells, 2024) The difference between traditionally used reactive methods and the more recent proactive methods is the nature of the indicators used. Handfield et al. (2019) introduce a data analytics transformation figure, including data levels, that can be connected to the existing data in the SPM context (figure 5). The figure consists of a timeline of data, along with the analysis performed at each level.

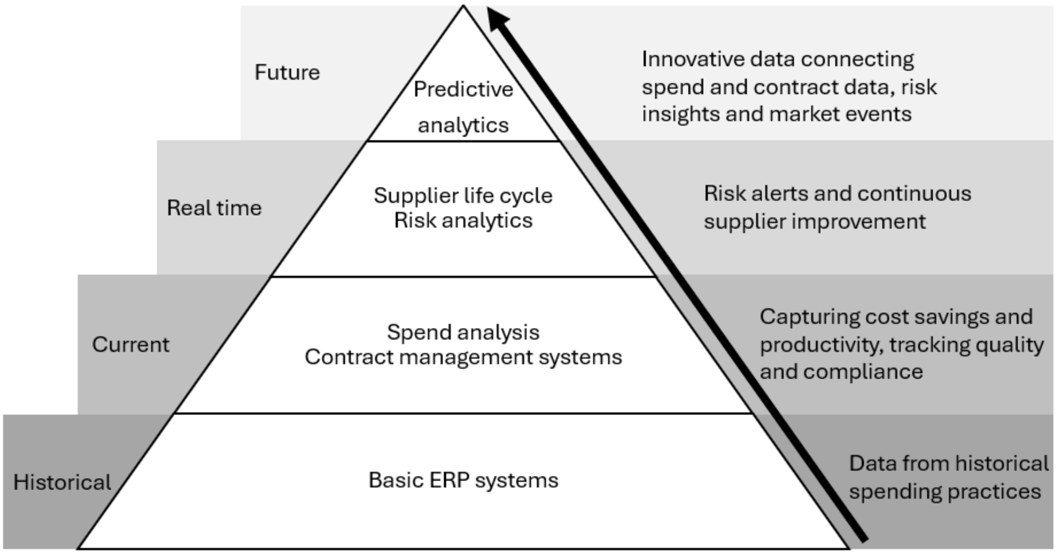

Figure 5. Supplier data transformation (modified from Hallikas et al. 2021; Handfield et al. 2019).

As Handfield et al. (2019) states the triangular shape of the model is based on the availability and usage of data currently, mentioning especially the limited amount of data regarding predictive analytics. Previously, organisations have relied on historical data generated from ERP systems, consisting, for example, of previous spend or incidents. However, PSM has managed to reframe analysis to consider a wider perspective of information, now extending to more predictive measurement through real-time and futuristic data. For decisionmakers it is essential to learn how to deal with real-time data that steadily flows into the organisation and process it fast into decisions. (Handfield et al., 2019) Predictive analytics refer to analysing the future of operations (Handfield et al., 2019) by connecting data types and information together, rather than tracking historical metrics as a single entity (Hallikas et al., 2021).

Predictive analytics is a subset of data analytics and data science, and in it can be used as a way to integrate quantitative and qualitative analysis together. Proactive methods, on the other hand, refer to utilising predictive analytics, instead of focusing on the previously traditional, backward-focused indicators (Zheng et al., 2019), which only provide information regarding past operations. Zheng et al. (2019) additionally discuss that in overall business performance management, proactive measurement uses leading indicators to potentially predict the future and the outcome of the operations. Regarding logistics and SCM, predictive analytics and leading indicators used for proactive methods actively create potential for the use of textual data and its analysis. (Hallikas et al., 2021; Waller & Fawcett, 2013) Therefore, as qualitative data analysis usually supports proactive measurement and information generation (Jiang et al., 2024), a connection between predictive analytics, proactive methods, leading indicators, and qualitative data, can be created. That said, the transformation towards more predictive data analysis is happening, with the goal to acquire more proactive operations and measures in supply chain context. As stated, this thesis connects leading indicators, proactive measurement, and the use of qualitative data into a single approach. This means that proactive measurement in this thesis is seen to consist of qualitative measures and data, which with the utilisation of technology, can be even further improved and integrated into use in the procurement function of organisations.

2.4 Digitalisation and digital transformation in supply chains

According to Jahani et al. (2021), P4.0 adds visibility, resilience, and value to supply chains and procurement, thus improving their performance. Supply Chain 4.0, on the other, hand refers to enabling flexible, autonomous, and dynamic supply chains through the use of digital technologies (Da Silva et al., 2019; Zekhnini et al., 2020). These digital changes and improvements in procurement and supply chains can further enhance the effectiveness or competitive advantages of various functions, such as lead times (Jahani et al., 2021) or information flows (Bag et al., 2020). What comes for procurement process success, technology use, and integrated IS can be seen as measures that improve it (Brandmeier & Rupp, 2010). Büyüközkan & Göçer (2018) also state that digitality can be seen to make supply chains faster, more flexible, globally connected, eco-friendlier, innovative, scalable, and intelligent, while also enabling real-time or proactive actions.

Digital transformation is a continuous process that improves or replaces organisational processes and structures, as well as PSM (Warner & Wäger, 2019). As digitalisation can be defined as the acquisition of different IT into organisational use, digital transformation, on the other, hand works as a wider, more transformative set of actions. Digitalisation and digital transformation have worked as drivers of P4.0 and I4.0. Viale & Zouari (2020) introduce digitalisation in the procurement context as the means of adapting IS and IT, along with the necessary human resources and skills to move procurement towards digital procurement.

Supply chain process digitalisation involves the acquisition of technology and digital tools to facilitate various material and information flows throughout the supply chain (Büyüközkan & Göçer, 2018; Patrucco et al., 2020), thereby expanding the scope of inspection. According to Hallikas et al. (2021), digitalisation can be observed in the process through e-sourcing, e-tendering, and enterprise resource planning (ERP). The mentioned technological systems support the specification phase, selection phase, and the creation and approval of requisitions and finally the ordering (Hallikas et al., 2021). For specification and tendering, through e-auctioning, digital RFX documents, such as request for information (RFI), can be used (Hallikas et al., 2021; Srai & Lorentz, 2019).

Additionally, Lorentz et al. (2021) introduce categories in which technology use can be categorised in. These categories are communication support, process structuring, information processing, and decision aiding (Lorentz et al., 2021). Handfield et al. (2019) focus on analytics and distinguishing use cases such as spend management, inventory management, and project management. These are available through technologies, such as cognitive analytics, data analytics, and cognitive computing, cloud-based technologies and system bolt-ons, which are used in, for example, ERP and customer relationship management (CRM) systems to capture data or extend the system (Handfield et al., 2019). Figure 6 visualises how IS and e-procurement are combined into the procurement process.

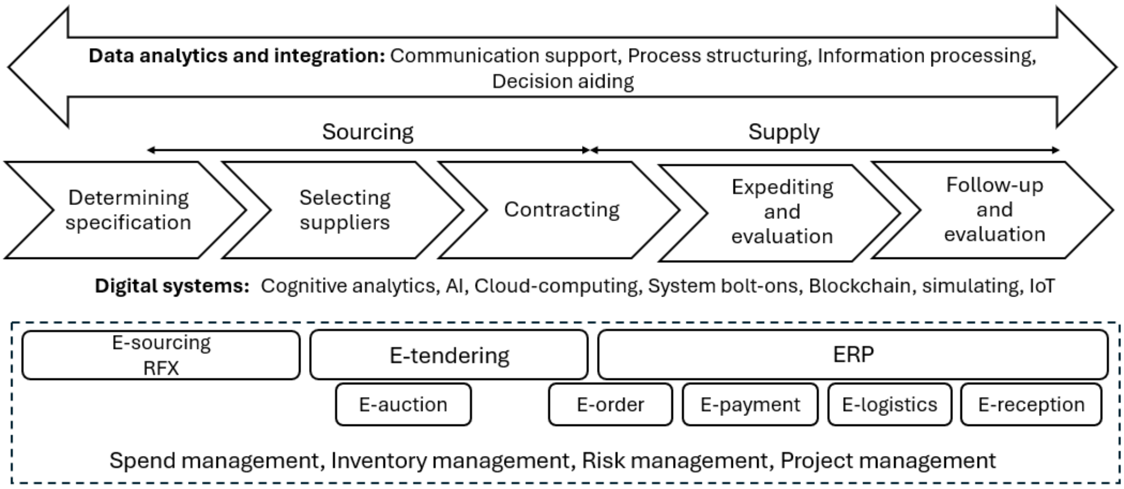

Figure 6. Digitality in procurement (modified from Hallikas et al. 2021; Handfield et al. 2019; Jahani et al. 2021; Weele 2018).

The PSM function has become more efficient, automated, and optimised, all while maintaining cost reductions (Srai & Lorentz, 2019). Technologies related to PSM digitalisation include IoT, cloud computing, Big data analytics (BDA), AI, mobile technologies, virtual reality or augmented reality, blockchain, and automation (Lorentz et al., 2021; Srai & Lorentz, 2019). From these technologies, AI, blockchain, BDA, IoT and cloud computing can be seen as the most applied (Da Silva et al., 2019; Jahani et al., 2021; Srai & Lorentz, 2019; Zekhnini et al., 2020). The improvements proposed by these technologies include cost reduction, security enhancement, performance improvement, sustainability development, improvement in information and data sharing, and supplier selection, evaluation and performance management (Jahani et al., 2021). In addition, Srai & Lorentz (2019) introduce value drivers in process improvement and innovation, relationship management, supply market knowledge management, and coordination and control.

Srai & Lorentz (2019) introduce a PSM digitalisation grid that visualises the use cases of P4.0 technologies in PSM and combines these with procurement value drivers. In the grid, the rows represent the different practices, while the columns consist of the various technologies. In this thesis, the focus is on the advanced technologies mentioned, although basic technologies, such as the internet, PCs, social media, and smartphones have been considered as part of it in some sources (e.g. Büyüközkan & Göçer, 2018; Srai & Lorentz, 2019; Warner & Wäger, 2019). Since the focus is on nonrelational PSM practices, figure 7 visualises those, the most applied technologies, and the improvements.

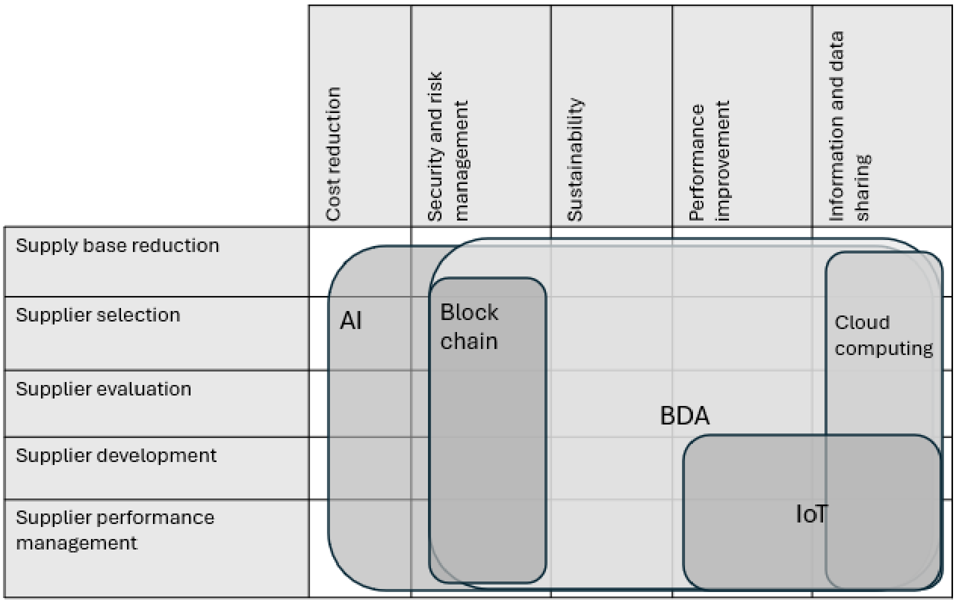

Figure 7. Nonrelational PSM practice technology grid (based on Helo & Hao 2022; Karttunen et al. 2023; Srai & Lorentz 2019; Zimmermann & Foerstl 2014).

According to Srai & Lorentz (2019), these technologies help manage costs, add security, develop risk management and sustainability, and improve the performance and efficiency of the practices. Blockchain enables more visibility and traceability, adding to the use of supply analytics, such as sustainability and risk management. (Karttunen et al., 2023; Srai & Lorentz, 2019) Additionally, AI, machine learning, and cognitive computing can be utilised to provide advisory recommendations and aid in decision-making (Helo & Hao, 2022; Srai & Lorentz, 2019; Wang et al., 2016).

2.5 Artificial intelligence methods in supply chains

Through the introduction of digitalisation, AI has been generalised in supply chains and SCM. Due to its widespread utilisation in various fields, AI as a technology is considered a general-purpose technology (GPT) and is therefore briefly compared to historically significant technologies (Crafts, 2021). GPTs usually significantly change operations and procedures (Grashof & Kopka, 2022).

The defining efforts of AI started as early as the 1950s (Neapolitan & Jiang, 2018). What comes to modern definitions, according to Guida et al. (2023) AI as a term refers to a significant part of computer science, which examines the use of computers and software capable of human-like operations. In addition, Ma et al. (2024) introduce AI as the study and effort to make computers match or surpass human intelligence, precision, and speed. AI is not only concerned with understanding but also with designing and building intelligent machines and computers (Russell et al., 2022). In practice, AI techniques assist human personnel in their tasks or free them up to take on other tasks where human expertise is needed. In some cases, human personnel's tasks may involve monitoring and controlling of AI algorithms and their work (Sergi et al., 2019).

Pournader et al. (2021) introduce AI branches, such as Machine Learning, Expert systems, Vision systems, Speech recognition, and simulation and modelling. This division is supported by Helo & Hao (2022), who introduce the techniques as enablers of an intelligent system, thereby including robotics, Neural Networks, Natural Language Processing, and speech recognition and processing. Introducing AI as the result of a continuum of analytics, Davenport (2018), on the other hand, discusses Natural Language Processing, Neural Networks, and Machine Learning. The following table 8 introduces traditional AI techniques and their intended use cases.

Table 8. AI techniques and their intended applications.

AI technique	Application	Source
Machine Learning	Prediction, pattern recognition, automating processes	Davenport, (2018); Helo & Hao, (2022); Pournader et al., (2021)
Expert systems	Problem solving, design-based negotiations	Helo & Hao, (2022); Pournader et al., (2021); Schulze-Horn et al., (2020)
Neural Network	Pattern recognition, characterisation of situations, processing abstract information	Davenport, (2018); Helo & Hao, (2020)
Vision systems	Identifying and processing features in videos and images, capturing and interpreting images intelligently	Helo & Hao, (2022); Pournader et al., (2021); Schulze-Horn et al., (2020)
Robotics	Automating structured tasks	Helo & Hao, (2022); Schulze-Horn et al., (2020)
Natural Language Processing	Statistical analysis of qualitative data, information extracting from words and phrases in text	Davenport, (2018); Helo & Hao, (2022); Pournader et al., (2021); Trappey et al., (2020)
Speech recognition and processing	Converting speech to text, voice-driven applications	Fu & Sun, (2018); Helo & Hao, (2022); Pournader et al., (2021)
Simulation and modelling	Prediction, intelligent planning, event simulation	Pournader et al., (2021); Schulze-Horn et al., (2020); Trappey et al., (2020)

Pournader et al. (2021) categorise AI methods in the supply chain context into a higher-level categorisation that includes sensing and interacting, learning and decision-making. Similarly, Yang et al. (2021) mention AI to be used specifically in procurement decision making. However, Helo & Hao (2022) deepen the framework by focusing on more specific use cases and classifying them according to certain business purposes. Discussing more specific use cases, Jahani et al. (2021) mention AI being used, for example, in autonomous vehicle routing, lot sizing and warehousing, and in searching for prospective suppliers. Meyer & Henke (2023) combine AI into the PSM process and introduce different use cases through the model. To follow the Meyer & Henke (2023) model and deepen the analysis further, examples of AI use cases connected to the procurement process are introduced in figure 8.

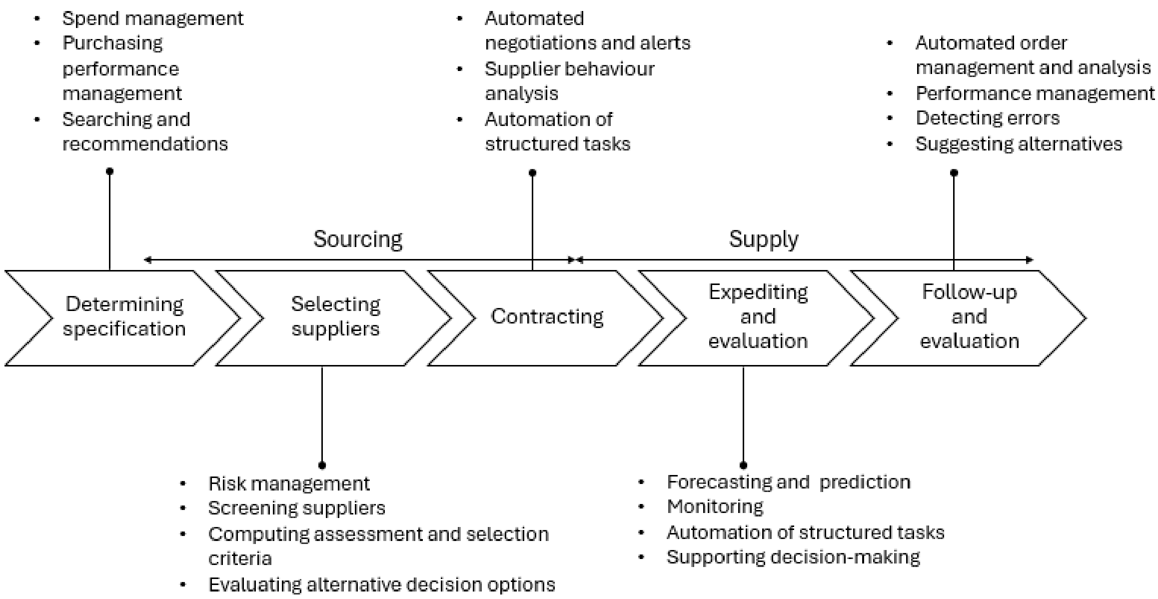

Figure 8. Examples of AI applications in the PSM process (based on Helo & Hao, 2022; Jahani et al., 2021; Khedr & Rani, 2024; Meyer & Henke, 2023; Pournader et al., 2021; Schulze-Horn et al., 2020).

It is important to note that it is normative to combine multiple techniques to create a system that enables the desired outcome (Helo & Hao, 2022). However, according to Trappey et al. (2020), techniques focusing on qualitative data tend to require more testing and validation regarding reliability, creating the need for additional resources. Applications analysing qualitative data also require large amounts of data from which to learn, making the implementation of said models previously difficult in the context (Davenport, 2018).

2.6 Natural Language Processing

Natural Language Processing (NLP) refers to an AI program or script that processes or generates written or spoken natural language, with the purpose of performing useful tasks (Deng & Liu, 2018; Steinkamp & Cook, 2021). The significant difference to traditional AI applications is therefore the form in which the data is. The aim of NLP is to enhance communication between humans or between humans and computers, or to improve data gathering processes, including the collection of qualitative data (Hirschberg & Manning, 2015). As a study, NLP combines computer science, mathematics, and linguistics. Two main directions of NLP research are Natural Language Understanding (NLU) and Natural Language Generation (NLG) (Kang et al., 2020), which generally refer to understanding and comprehending natural language, as well as generating the corresponding data. As briefly introduced in the previous sub-chapter, the aspect that distinguishes NLP from other AI applications and data processing systems is the usage of knowledge of language (Jurafsky et al., 2000). This means that in addition to counting and processing the data, the algorithms must have knowledge of the words and their meanings.

Machine Learning (ML) is one of the AI techniques that have enabled the use of NLP (Kang et al., 2020). ML refers to systems and techniques used to teach machines how to mimic human behaviour, automatically analyse data, and extract information from it (Steinkamp & Cook, 2021; Tirkolaee et al., 2021). ML is connected to NLP, since ML techniques such as supervised learning or semi-supervised learning (Gazit et al., 2024; Tirkolaee et al., 2021) can be used behind NLP techniques. General ML has been human-designed, and it requires significant levels of human expertise to use and develop. To remove the bottleneck of human engineering, a layered model structure called Deep Learning (DL) has emerged (Deng & Liu, 2018). Most of the modern NLP applications use DL techniques, but ML and DL are not used in all NLP (figure 9).

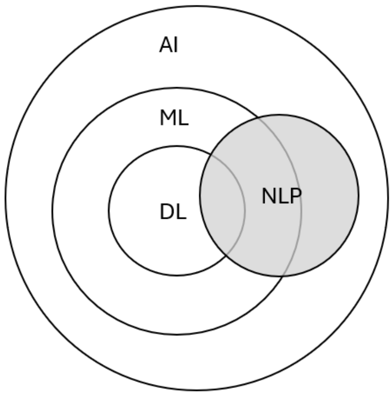

Figure 9. NLP's relation to AI technologies (modified from Gazit et al., 2024; Steinkamp et al. 2021).

DL is therefore a section, or subcategory of ML. DL refers to techniques that make decisions based on complicated algebraic models, known as neural networks, that consist of connections that can be strengthened or weakened to tune its learning abilities (Russell et al., 2022). This means that the data passes through multiple network layers before being transformed into the final output of the program. A simplified DL neural network can be seen in figure 10. The comparison of DL to ML can be interpreted from the names, as DL usually has more layers of circuits and connections (Neapolitan & Jiang, 2018), compared to ML, and it can more efficiently and independently work with the input data.

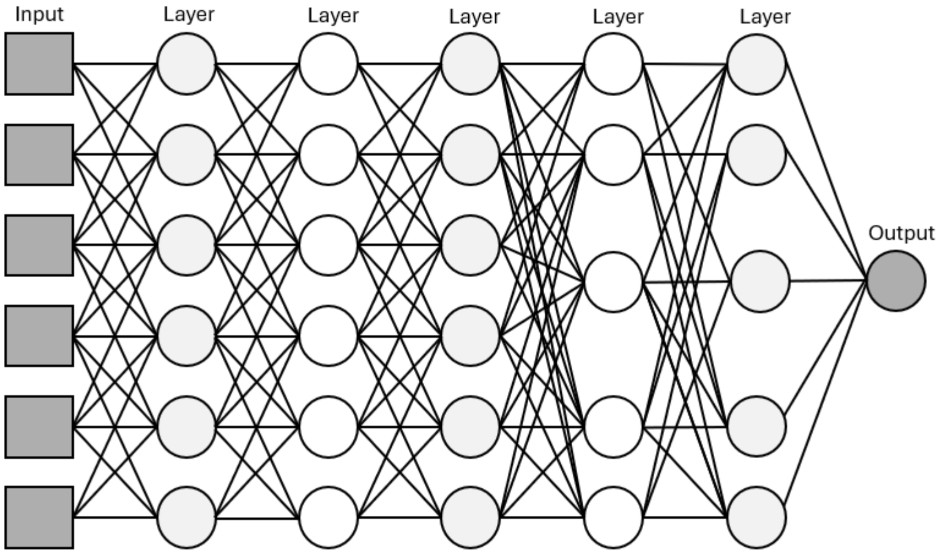

Figure 10. A simplified Deep Learning neural network model (modified from Russell et al. 2022).

Nevertheless, as mentioned, more traditional NLP applications, such as a rule-based method (figure 11), which are not based on the use of DL, exist. The decision list functionally moves towards the target output by using commanded rules to classify data based on predictors (Neapolitan & Jiang, 2018; Russell et al., 2022) Additionally, linear regression is one of the traditional and simple models.

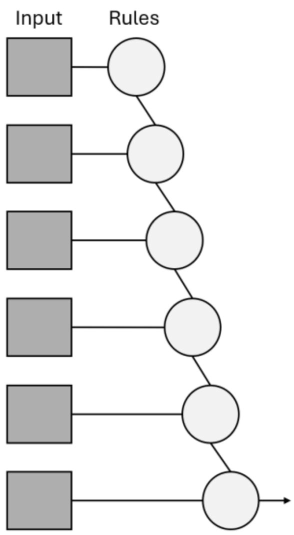

Figure 11. A Simplified Decision list (modified from Russell et al. 2022).

Earlier development of NLP has been based on knowledge-based AI programs that can be used to solve simple or narrow problem, through a technique called the head-tail method. Head-tail methods are built by humans by identifying the head parameters and leaving the tails for the program to solve, therefore creating a system that combines different parameters as individual pairs. (Deng & Liu, 2018) This technique been has further developed into other probabilistic and rule-based methods (Kang et al., 2020).

2.6.1 Natural language analysis process

According to Kang et al. (2020), NLP follows a data analysis process that can be divided into preprocessing, text representation, and algorithms. In addition, Steinkamp & Cook (2021) introduce the following process steps: task specification, data collecting and cleaning, data annotation, algorithm building and training, and algorithm evaluation. On the other hand, Wu (2024) introduces a more iterative process that moves from algorithm training back to text processing and vice versa. Overall, the general process can be divided into the following steps: data collecting, data processing, data representation, and algorithm utilisation. The general process is visualised in figure 12. From the mentioned steps, the first two are included by Kang et al. (2020) in preprocessing, data representation in text representation, and the final two steps are included in the algorithm category. Neapolitan & Jiang (2018) further deepen the process of data processing by introducing three general steps: data parsing, semantic interpretation, and contextual interpretation.

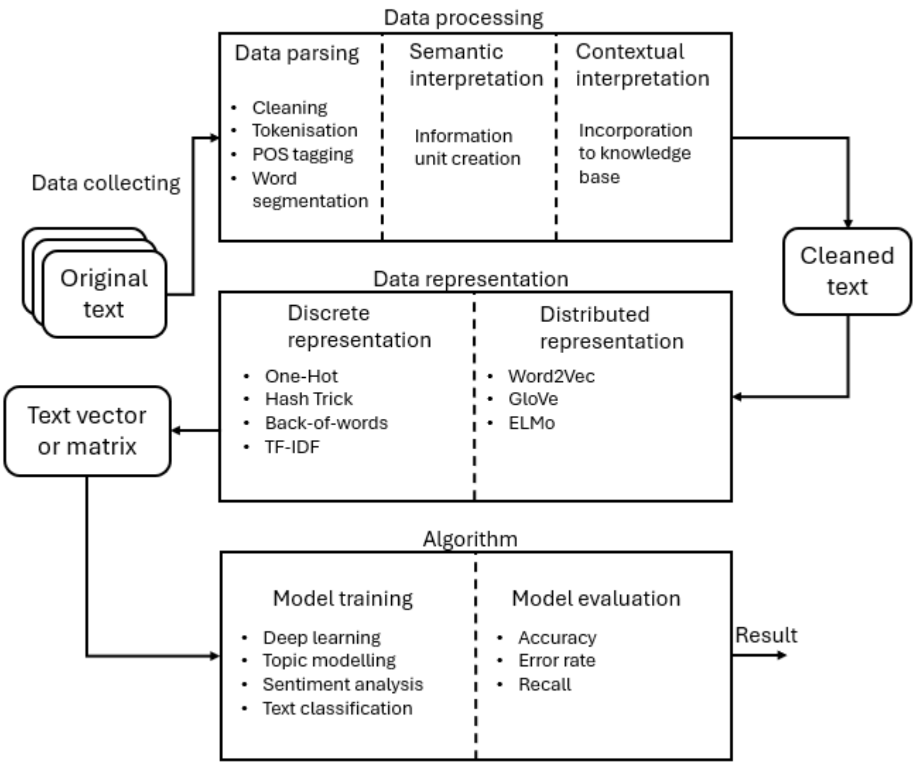

Figure 12. Simplified, general NLP process (modified from Deng & Liu 2018; Kang et al. 2020; Neapolitan & Jiang 2018).

Data parsing consists of data cleaning and data tokenisation, which refers to the process of breaking the input text into units of words or sentences (Kang et al., 2020). Another parsing technique, called Word segmentation, is closely related to data tokenisation (Deng & Liu, 2018). Semantic interpretation refers to understanding the meaning a the word while contextual interpretation refers to understanding the context and incorporating the word into the knowledge base (Neapolitan & Jiang, 2018). In addition, Kang et al. (2020) mention encoding, which is done before data processing to ensure that the data is in the right form regarding character encoding.

Data representation further analyses the text through different mechanisms for the algorithms to understand it (Kang et al., 2020). Data representation consists of distributed and discrete representations. The goal of distributed representation is to understand a word's meaning based on the words frequently appearing close (Kang et al., 2020), while discrete representation focuses on representing the data in a certain way, such as binary vectors, integers, or other symbols (Deng & Liu, 2018). In distributed representation, techniques such as Word2Vec (Mikolov et al., 2013), Global Vector (GloVe) (Pennington et al., 2014), and ELMo (Peters et al., 2018) are used by researchers to capture word meanings in their context. On the other hand, discrete representation encompasses techniques such as one-Hot encoding, bag-of-words (BOW), the Hash Trick, and frequency-inverse document frequency (TF-IDF) (Kang et al., 2020). One-hot is referred to as a more traditional encoding since it creates a set of unique words that it later sorts and indexes. Additionally, a Bag-of-words is a more concise representation that includes whole sentences in the analysis. (Patil et al., 2023) TF-IDF examines the frequency and importance of a specific word, and, in addition to previous methods, also compares it to other text materials (Kang et al., 2020; Patil et al., 2023). Hash Trick refers to text dimension reduction, in which the text is transformed from multi-dimensional matrices into smaller-scale vectors for the algorithm to take in (Kang et al., 2020).

The algorithm model training depends on the used algorithm. Evaluation, on the other hand, can be done using familiar parameters, such as model accuracy, error rate, and recall needs, and it is done iteratively, both with test sets and official datasets (Kang et al., 2020; Steinkamp & Cook, 2021).

2.6.2 Natural Language Processing applications

Khurana et al. (2023) introduce NLP applications, such as Machine Translation, Text Categorisation, Summarisation, and Dialogue Systems. Hirschberg & Manning (2015) support this by adding conversational agents, Machine Reading, Data mining, and analysis and generation of speaker states into the list. Kang et al. (2020) introduce a more concrete approach by dividing different applications based on their traditional fields in business management. Information extraction, text-pattern recognition and categorisation are mentioned as methods recognised in operations management (Kang et al., 2020). The NLP applications can be grouped based on their functionalities (table 9).

Table 9. NLP classifications, applications and their definitions.

NLP group	NLP application	Definition	Sources
Text analysis and understanding	Information extraction	Identifying interesting entities, words and phrases from natural language.	Khurana et al., (2023)
	Text categorisation	Assigns and filters large datasets to predefined categories based on different rules and permissions.	Khurana et al., (2023)
	Text-pattern recognition	Detecting patterns in natural language such as semantics or repetition.	Kang et al., (2020); Min et al., (2024)
	Data mining and analysis	Analysing large amounts of textual data and examining relations.	Hirschberg & Manning, (2015)
Text generation and translation	Text summarisation	Summarising text while including the original meaning.	Hirschberg & Manning, (2015); Khurana et al., (2023); Min et al., (2024)
	Generation and analysis of speaker states	Identification and analysis of sentiment and emotion. Generating and assessing positive and negative sentiments.	Hirschberg & Manning, (2015)
	Machine translation	Translating words and phrases from one language to another.	Hirschberg & Manning, (2015); Khurana et al., (2023); Min et al., (2024)
Interactive systems	Conversational agents and dialogue systems	Identifies natural language and completes simple tasks for humans.	Hirschberg & Manning, (2015); Khurana et al., (2023)
	Machine reading	Analyses large sets of texts to create a knowledge base and answer questions based on it.	Hirschberg & Manning, (2015)

Chiu & Lin (2018) introduce how information extraction is used to identify key concepts in user reviews. Similarly, Balan et al. (2024) utilise it to extract sustainability topics from technical documents and news articles. Data mining and analysis can be used to scrape data from social media, market reports, news articles, or reviews, therefore greatly broadening the number of available data sources of natural language (Hirschberg & Manning, 2015; Meyer & Henke, 2023). Tavana et al. (2022) utilise text mining from different databases in supply chain context.

An example of text categorisation is Email filtering, while text-pattern recognition can be used to prediction, (Min et al., 2024) or to find and connect certain entities from data (Kang et al., 2020). Tetlock et al. (2008) introduce an example of how text-pattern recognition and sentiment analysis is used to interpret negative wordings from press releases, to predict low performance earlier than quantitative measures indicate. Jurafsky et al., (2000) introduce the idea that in a business context, text summarisation can be used to summarise text from reports or to create meeting transcripts. Jha et al., (2022) also analyses NLP applications in generating summaries from business meetings.

Current machine translation applications allow instant translation from one language to another, and with DL-based models, the algorithms can capture semantic similarities and intermediate representations, while considering grammar and sentence structure (Hirschberg & Manning, 2015; Khurana et al., 2023). Treiblmaier & Mair (2021) introduce the utilisation of machine translation to translate company interviews. Generation and analysis of speaker states, on the other hand, can recognise opinions, speculations, and negative or positive tones from text data, which can for example be Emails, reviews, or social media posts. (Chae, 2015; Hirschberg & Manning, 2015)

A developed version of conversational agents or dialogue systems can maintain conversations, identify dialogue acts, and even analyse the user's messages while they are being written. A remarkable feature is the ability to entrain to the user's pronunciation and word choices, making the agents a human-like conversational partner. (Hirschberg & Manning, 2015; Khurana et al., 2023) Another insight is the ability to memorise prompts and use them to broaden the knowledge base (Min et al., 2024). The use of AI agents has been explored in various contexts, including marketing, transaction management, and operations management, with potential applications in supporting decision-making (Korzynski et al., 2025; Mariani et al., 2023).

NLP use cases are categorised in table 10. While they are introduced as individual technologies, it is essential to understand that typical applications often involve the use of multiple NLP technologies. For example, Khurana et al. (2023) introduce combinations such as sentiment analysis and text classification, as well as text summarisation and machine translation. Kang et al. (2020) introduce combining NLP with manual work, with an example of text-pattern recognition and manual inspection.

Table 10. Examples of NLP use cases in business.

NLP application	Use case in business context	Sources
Information extraction	Finding key concepts from user reviews Extracting certain topics from documents and publications	Balan et al., (2024); Chiu & Lin, (2018)
Text categorisation	Categorising large topics	Treiblmaier & Mair, (2021)
Text-pattern recognition	Interpreting negative words from publications	Tetlock et al., (2008)
Data mining and analysis	Web crawlers in social media, market reports and news articles Analysing large databases	Hirschberg & Manning, (2015); Meyer & Henke, (2023); Tavana et al., (2022)
Text summarisation	Summarising reports and business meetings Creating meeting transcripts	Jurafsky et al., (2000); Jha et al., (2022)
Generation and analysis of speaker states	Analysing sentiment in social media	Chae, (2015)
Machine translation	Translating meetings or interviews	Treiblmaier & Mair, (2021)
Conversational agents and dialogue systems	Supporting decision-making and optimisation in marketing, transaction management and operations management	Korzynski et al., (2025); Mariani et al., (2023)
Machine reading	Question answering and fact extracting	Hirschberg & Manning, (2015)

Another example of a model combining multiple techniques is a Large Language Model (LLM), which according to Gazit et al. (2024), has revolutionised the field of NLP by offering excellent proficiency regarding interactions with natural language. LLM models are able to simultaneously understand and generate natural language, as well as maintain conversations with the users, based on the large amount of text data and parameters they are trained on. LLM's can be seen to perform significantly more efficiently when compared to traditional language models (LM), as they typically utilise deep neural networks to perform tasks. (Gazit et al., 2024; Min et al., 2024)

3. RESEARCH METHODOLOGY

Based on a research continuum by Saunders et al. (2019), this master’s thesis, in its context, objectives, and purpose, falls between basic research and applied research. This is because the research has effects in its purpose, context, and impact in both of the categories presented by Saunders et al. (2019), placing the thesis in the middle of them. Combining this with the description of the categories by Dubey & Kothari (2022), the thesis falls more under basic research, since the problems addressed were not posed by a sponsoring agency.

This master’s thesis is a business and management research that aims to systematically examine and generate knowledge and information, which can be utilised in an organisation’s business decisions (Dubey & Kothari, 2022; Saunders et al., 2019). The prime objective of business research is to provide information and research to help organisations answer questions related to operational, tactical, or strategic levels of business (Hair et al., 2023), which in the case of this thesis focuses on strategic procurement and SPM.

3.1 Research strategy and approach

Saunders et al. (2019) introduce research philosophies that work as a system of assumptions or realities that, during the research process and knowledge development, shape the understanding of, for example, the research questions or how the findings are interpreted. Based on the research subject, research questions, and context, the research philosophy of this master’s thesis is pragmatism. The decision is made based on the nature of pragmatism, which according to Saunders et al. (2019), indicates that the research aims to contribute by creating informative and practical solutions for a recognised problem. Additionally, according to Elkjaer & Simpson (2011) pragmatism is a practical philosophy, and from that perspective, it offers a way to approach and understand questions such as “how” and “why”. However, this research also exhibits features of interpretivism. In interpretivism, it is typical for the researcher’s beliefs and interpretations to be visible in the research results (Saunders et al., 2019), which in the case of this research is natural due to empirical research consisting of interviews.

The research uses abductive an approach. An abductive approach is a combination of deductive and inductive approaches. In a deductive approach, the researcher starts with a theory generated from theoretical research and then tests it by collecting data. On the other hand, an inductive approach typically starts by collecting data and then moves on to build theory around it. (Hair et al., 2023; Saunders et al., 2019) Since this research combines findings from published theoretical literature with empirical data, and therefore creates new theories based on existing theory and new observations, it employs an abductive approach.

This master's thesis is conducted as qualitative research. Qualitative research is based on non-numerical data and assesses attributes, preferences, and opinions, aiming to understand the features and qualities of the researched phenomenon to fill the recognised information gap (Dubey & Kothari, 2022; Saunders et al., 2019). This methodological choice is made since the objective of this research is to gain an in-depth understanding about insufficiencies, information needs, and the possibilities of NLP in SPM. As the research does not specifically contain numerical data, the qualitative research method is considered appropriate. A multi-method research indicates to using more than one method of data collection (Saunders et al., 2019), and therefore this research is categorised as one.

The chosen research strategy is grounded theory (GT). GT-method refers to creating theoretical explanations of phenomena and interpreting their meanings in specific situations. Data collection and analysis in GT is typically done throughout the whole research process, and the researcher is actively participating in the context of the study. (Dubey & Kothari, 2022; Saunders et al., 2019) The methodological choices are summarised in figure 13.

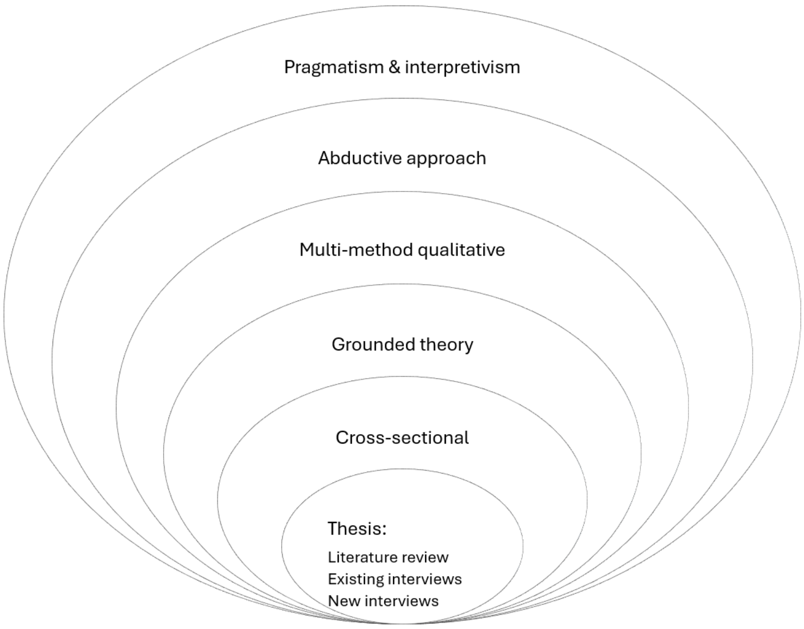

Figure 13. Onion model of the research (modified from Saunders et al. 2019).

Saunders et al. (2019) introduce two different time horizons for research: cross-sectional and longitudinal studies. As seen in figure 13, the time horizon of the master's thesis is cross-sectional. Cross-sectional studies are typically conducted only once at a particular time and about a specific phenomenon, and the data is typically collected over a short time period. (Dubey & Kothari, 2022; Saunders et al., 2019) Therefore, in this research, the data is collected and analysed at a certain time, without researching the future changes of the phenomena or repeating the research over time.

3.2 Sample and data collection

This master's thesis contains empirical data collected from two sources, all done in the AI-SIM project:

- Previous interview transcripts, and
- Interviews conducted during the work process of this thesis.

The following sub-chapters introduce first the overview of the data analysis, before moving forward to deeper introduction of the mentioned data sources and the significance of them in this research. In the final sub-chapter, data analysis methods are introduced.

3.2.1 Overview

By conducting the literature review and the empirical research simultaneously, the researcher was able to find connections and relevant information gaps through the data. The data analysis during the research followed an iterative pattern (figure 14) in both the literature and empirical analyses.

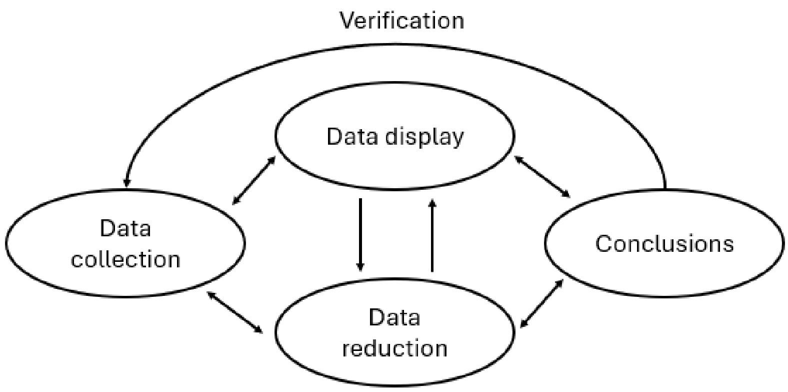

Figure 14. Data analysis process steps (modified from Hair et al. 2023).

The empirical research started by analysing the previous interview materials. Then, the analysis proceeded to the new interviews. The previous interviews were used to gain a comprehensive understanding of the existing supplier information needs in large manufacturing companies. This information was utilised as a basis for the new interviews, which even further focused on different data needs and AI potential regarding SPM. Therefore, the new interviews were conducted to deepen the already gathered information and to combine the recognised information needs into NLP use cases.

A conversation between two or more persons, that's done with a clear purpose and in which the interviewer asks subject-related questions in an unambiguous manner, is called a research interview (Saunders et al., 2019). Research interviews are an effective way to understand behaviour, relationships, and experiences through open-ended questions (Dubey & Kothari, 2022). As introduced, this thesis uses interview materials collected from two sources. Since both interviews have key questions that are used to guide the conversation, but still give space for more informal conversation (Dubey & Kothari, 2022; Saunders et al., 2019) they are classified as semi-structured interviews.

Semi-structured interviews are done under tighter control and initiative, and they follow a structure of certain themes and questions that have been decided by the researcher, while still allowing broader conversations around the subject (Dubey & Kothari, 2022; Saunders et al., 2019). The interviewees were chosen by non-probability sampling methods, as a full list of the research population was not available. In this research, purposive sampling and snowball sampling were used to find interviewees. Purposive sampling refers to the selection of interviewees based on specific characteristics that are believed to be representative of the total population (Dubey & Kothari, 2022). This indicates to the interviewees all being professionals in procurement, with possibly some experience regarding AI and technology. Snowball sampling refers to using current contacts, or the current interviewees, to find possible candidates to participate in the research (Dubey & Kothari, 2022).

By using this interview method, the researchers are able to concentrate more on what the interviewee sees as relevant and converse about areas around the subject that might not have been discussed earlier (Saunders et al., 2019). Semi-structured interviews also give researchers the opportunity to ask follow-up questions or other unanticipated questions related to the subject, resulting in insightful findings (Hair et al., 2023). As the subject of the research is complicated and interviewees might have different thoughts that can be influenced by personal or organisational views, as well as by the state of technology use in the case organisation, semi-structured interviews were deemed suitable. Also, since semi-structured interviews are flexible regarding the location where they are conducted (Hair et al., 2023), they were chosen as the data collection method.

3.2.2 Existing interview transcripts

The previous interviews were conducted by other researchers in the spring of 2024 as part of the AI-SIM project. The interviewees are from manufacturing companies that operate as potential users of AI solutions and as digital service providers. These interview materials have been partly used in a master's thesis by Kyntäjä (2025) and in other research articles under the AI-SIM project. The objective in using the existing interview transcriptions is to understand the basis of AI use in supply chains, but especially to learn about what kind of information is needed about suppliers and how performance management is done in different companies in Finland. For this thesis, the emphasis is on the different information and data needs that exist in supply chains. To use the existing transcriptions efficiently, it has been necessary and mandatory to analyse and study them thoroughly.

Interviewees have been divided into categories in advance based on their organisation's type in the supply chain context. The organisations utilising the technology are further divided based on their way of operating, dividing the interviewees into product and service providers. Based on the interviewee's business approach, they are categorised into continuous business organisations and project-based business organisations. The existing interview set consists of 28 interviews. Although, this thesis only utilises the interview transcripts of the manufacturing organisations that are solution users, narrowing the sample to 23 interviews. This decision was based on the scope of this thesis.

The research interview consists of questions regarding the interviewee's background, the organisation's background, and questions about the interview themes, such as the current solutions in SCM, information needs, and the potential of AI solutions. For this thesis, relevant questions are the following:

- What are the information needs related to procurement or Supply Chain Management that require supplier-related data?
- What type of information about suppliers is needed?

The chosen questions provide information regarding research question 2. The questions considering the information deficiencies in the supply chain and SPM create a base for this research, by supporting the analysis done on information deficiencies recognised by research literature. The information needs raised from the first interviews are also used as a guiding framework for assessing AI potential during the second interview round. The previous interviews have two different interview structures; one aimed at the solution providers and another at the users. Because of the chosen scope, only the latter of the structures is utilised. The structure's relevant part is included in Appendix A. Table 11 presents the interview data considering solution users, which includes the industries, size of the procurement organisation, number of suppliers and number of interviewees.

Table 11. Previous interview data: solution users.

Industry	**Size of procurement function (number of professionals)**	**Mentioned number of suppliers**	**Number of interviewees**
Machinery manufacturing	Over 500	Around 120	3
Mining and Industrial equipment	Over 30	Around 200	2
Industrial automation and Engineering	Around 1500	Thousands	2
Forestry and Paper products	Around 120	Around 15 000	2
Renewable energy and Chemicals	Over 100	Over 5000	2
Food and Beverage	Around 50	Around 4000	2
IT and Technical Engineering	Over 50	Around 10 000	2
	Only a couple	Thousands	2
	Around 10	Around 400	2
Power and Energy	Around 60	Around 10 000	2
Logistics Services	Around 30	Around 4000	2

The existing transcripts have been transcribed by previous researchers. The coding process was done cooperatively by the researcher of this thesis and another project researcher, by using ATLAS.ti -website. After briefly analysing the transcripts during the coding process, the transcripts were analysed again, and relevant parts were excluded to Excel sheets for deeper examination and translating, and to finally use in the work process of this thesis.

3.2.3 New interviews

The interview sample consists of large Finnish manufacturing organisations. From these companies, professionals working in supply chains and SCM were identified and selected. Before the search process, different employee titles were determined, and those identified as relevant to the research were used as search parameters. The possible interview candidates were found through search engines and finally added to an Excel sheet. To seek out more possible interviewees, it was decided that after the interviews, the researcher would ask if the person knew any other possible candidates from their organisation, who would be interested in participating and would preferably have knowledge about the use of AI in the supply chain context.

The interviewees were contacted by Email and given information about the research project and the themes of the interview. A preliminary time slot of 1-1.5 hours and the possibility to choose between using English or Finnish language were introduced. The interviews were done by Microsoft Teams, and they were recorded, so that the interviewees did not need to, for example, write down notes simultaneously. Microsoft Teams extracted a text file from the interview, which was then further transcribed. The interview transcripts containing Finnish were translated into English with the use of Microsoft Copilot. Table 12 has interview information which consists of data regarding the interviewers and the interviews themselves. Both interviewees and organisations are coded, as well as the interviewers. The interviews were conducted by three interviewers: the researcher of this thesis (R1) and two other researchers working in the AI-SIM project (R2 & R3).

Table 12. Interview data.

Organisation ID	Interviewee ID	Interviewer	Language	Date	Duration	Transcript length
A	A1	R2	Finnish	9.6.25	50 min	17 pages
B	B1	R1	Finnish	27.6.25	63 min	15 pages
C	C1	R1	English	27.6.25	48 min	15 pages
D	D1	R1	Finnish	16.6.25	68 min	19 pages
E	E1	R1	Finnish	16.6.25	39 min	17 pages
F	F1	R3	English	19.6.25	39 min	15 pages
G	G1	R2	Finnish	26.6.25	55 min	19 pages
H	H1	R1 & R2	Finnish	2.6.25	73 min	20 pages
I	I1	R1	Finnish	13.6.25	55 min	13 pages
J	J1	R2	Finnish	23.6.25	52 min	19 pages
K	K1	R1 & R3	English	12.6.25	53 min	17 pages
L	L1	R2	Finnish	24.6.25	40 min	18 pages
M	M1	R1	Finnish	9.6.25	60 min	15 pages
N	N1	R2	Finnish	30.7.25	65 min	24 pages

More information about the interview organisations is categorised in the following table. Table 13 includes the industries of the organisations and information about the organisation's procurement function and suppliers.

Table 13. Organisation data.

Organisation ID	Industry	Size of procurement function (number of professionals)	Mentioned number of suppliers	Supplier base
A	Machinery and service	Around 50	Thousands	Emphasis on local suppliers. Specific products sourced from specific suppliers.
B	Steel	Around 80	Over 10 000	Mainly from Europe, USA and Mexico. Suppliers categorised by criticality.
C	Forestry and paper	Around 120	Over 10 000	Local and global suppliers varying in different sizes.
D	Machinery and service	Around 40	Thousands	Global suppliers, based on competitiveness and compliance.
E	Mining and industrial machinery	Several hundreds	Over 100	Global suppliers, identified by spend and technological classifications.
F	Industrial automation and engineering	Around 1500	Thousands	Partner, key and main suppliers all around Europe, Middle East and Africa.
G	Chemicals	Over 50	Over 10 000	Global, based on factory locations. Existing suppliers are usually prioritised.
H	Machinery and service	Over 200	Over 20 000	Global, diverse suppliers categorised by spend and tail spend.
I	Forestry and paper	Around 500	Around 20 000	Local suppliers are emphasised, but each manufacture region has own suppliers categorised by spend.
J	Industrial automation and engineering	Around 20	Around 200	Local and global suppliers, with emphasis in Eastern Europe and Asia.
K	Mining and metals	Over 10	Around 350	Mainly local suppliers, some global too.
L	Food and beverages	Around 50	Around 5000	Local and global suppliers, classified by criticality and strategic significance.
M	Mining and industrial machinery	Over 10	Over 40 000	Local and global suppliers, classified by criticality.
N	Forestry and paper	Over 500	Over 100	Mainly local suppliers with some global ones.

In addition, the following table 14 includes data regarding the interviewees and their position in the procurement context. If the position of the interviewee is more specific than a managerial position related to procurement, it is mentioned.

Table 14. Interviewee data.

Inter-viewee ID	Interviewee position	Experience in procurement (years)	Field of study
A1	Procurement manager	8	Master's in economics and business administration
B1	Procurement manager	18	Master's in economics and business administration
C1	Procurement specialist (communications and marketing)	2+	Two master's degrees in business
D1	Sourcing manager	18	Master's in industrial engineering and management, Local master's degree from Britain
E1	Sourcing manager	5,5	Master's in industrial engineering and management
F1	Development manager	10+	Master's in industrial engineering and management
G1	Development manager	7,5	Master's in business administration, with a specialisation in industrial management
H1	Procurement manager	28	Master's in economics and business administration
I1	Category manager	7	Master's in agriculture and forestry
J1	Procurement manager	10	Master's in industrial engineering and management
K1	Head of sourcing	17	Master's in computer science and mathematics
L1	Development manager	10	Master's in food sciences
M1	Sourcing manager	25	Bachelor's in mechanical automation engineering
N1	Procurement manager	20	Master's in environmental technology

The interview structure was developed in both English and Finnish, as the interviews are conducted in both languages. The interview structure consists of five themes and 20 questions overall. The themes transition from supplier capabilities into those regarding NLP and AI. Before the first interview theme, background questions about the interviewee and their organisation are asked, to gain an overview of, for example, the current procurement function of the organisation. At the beginning of the interviews, a quick conversation is also conducted to introduce the AI-SIM project, the researchers, and the goals of the interview to the interviewee.

The interview structure includes an appendix consisting of supplier performance aspects. This categorisation is based on the literature analysed in sub-chapter 2.3.1. The aim of this categorisation is to first assist the interviewee during the interview and second, to establish a cohesive linkage between the analysed literature and the empirical study. Because the structure is extensive and covers themes regarding the work of the other researchers of the project too, not all parts of it were utilised for this thesis. The complete relevant interview structure can be seen in Appendix B.

3.3 Data analysis methods

As the used method is qualitative analysis based on collected data, the objective is to understand the researched phenomenon and its nature (Dubey & Kothari, 2022; Saunders et al., 2019). The aim is to understand how medium to large-sized organisations use AI in their SCM, what challenges and qualitative data exist, and how NLP could be utilised. To successfully analyse data, it is important to become profoundly familiar with it. This can be done through interview transcripts and summarising. (Saunders et al., 2019) As mentioned by Dubey & Kothari (2022), qualitative research consists of systematically collecting evidence and producing findings. The technique used in this thesis involved iteratively reviewing the data, collecting insights and deepening the analysis based on them.

Although the previous interview transcripts had already been transcribed, they were coded to identify different themes for use in this research and in other research papers done for the AI-SIM project. The new interview transcripts were transcribed and coded. Coding was done with the help of ATLAS.ti-application. Coding and categorisation of open-ended interview questions is difficult, and therefore an inductive thematic coding strategy was utilised. This indicates that the coding was done based on different mentions of subjects that arose during the interviews. (Dubey & Kothari, 2022) This resulted in a large number of code labels recognising the important themes of the interviews. Saunders et al. (2019) suggest that inductive code labels can be rearranged into a hierarchical form to recognise relationships between categories, and therefore the technique was utilised in this research.

The transcripts were coded systematically. This indicates that not all codes were used for this thesis, but rather as a pathway to the ones that were utilised. The literature research was also used as a basis during the coding process. The first code groups are Current solutions used in procurement, Mentioned supplier performance aspects, Current challenges in SPM, Quantitative capability data, Qualitative capability data, and Potential general AI use cases in SPM.

Current procurement solutions were coded based on their intended use. If the solution included a generalised solution, such as ERP, that was used. The main goal was to examine whether AI and LLM solutions were already in use in the organisation. This code category also created insights into what has already been done regarding the existing challenges. Supplier performance aspects were coded by the capability categories. Challenges in SPM were coded based on the root cause, including, for example, resources or data inaccuracy. Further, the mentioned data needs were first divided based on whether they were qualitative or quantitative in nature. The quantitative data was coded based on what the data is related to as for example risks, quality, or operations. The qualitative data needs were coded by their data sources. This was done as the goal was to group the qualitative data needs into related capability fields, and this coding method enabled the researcher to later analyse the data sources in an easier way. Finally, general AI use cases were coded based on AI methods and the type of data. This was done based on what the interviewees mentioned; if a certain type of data, such as market or financial data, was mentioned, a code was created based on it, but otherwise, if the interviewee mentioned the use case on a more general level, such as automation or tracking, that was utilised. A complete tree model of the code groups can be found in appendix C.

The final code groups (figure 15) were built based on the capability categorisation introduced in sub-chapter 2.3.1. It is important to note that sustainability was grouped as one larger entity that includes both social and environmental sustainability. This decision was based on the broadness of the subject and the scope of this thesis, making it logical to focus on it as a whole. Every group included challenges, qualitative data sources, and NLP potential. This allowed the researcher to create a comprehensive categorisation of every aspect related to the capability categories and create cohesion between literature research and empirical analysis.

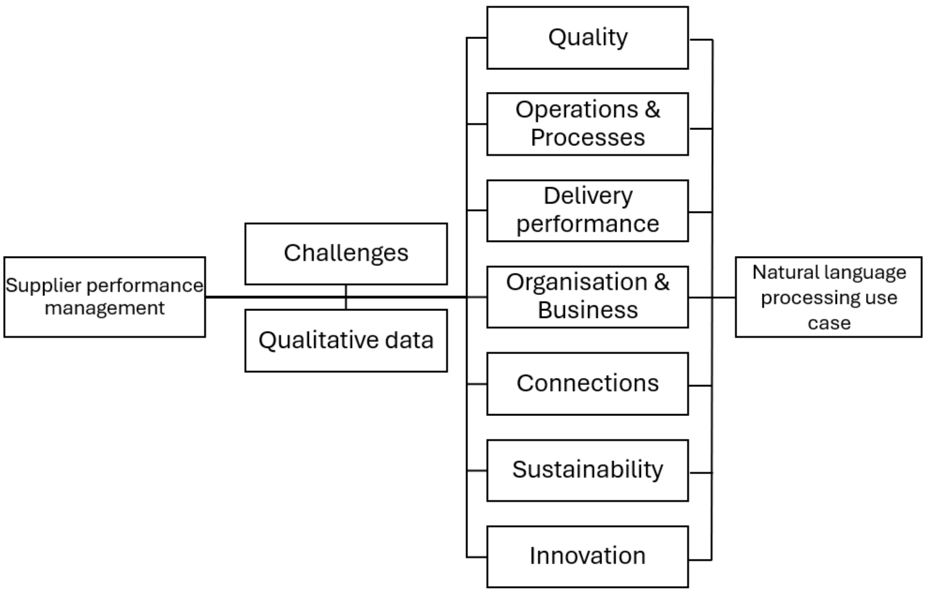

Figure 15. Tree-model of the final coding groups.

Every transcript is analysed as an independent object. The transcripts are analysed multiple time with different goals: first to get a general picture, then to code the significant themes and finally to find connections, cohesion and important findings regarding the thesis.

4. RESULTS

The empirical results obtained from the interviews are presented in this chapter. First, the current information needs in manufacturing companies are examined through the first interview round. This analysis is connected to the second research question. Then, based on the second interview round, supplier capability categories are introduced. The supplier capabilities are introduced through the framework built on existing literature, and the results are related to the third research question. The third sub-chapter focuses on challenges that the interviewees currently recognise regarding SPM. The fourth part introduces qualitative data that exists in SPM, and finally, the recognised potential NLP use cases are introduced. The results regarding the NLP use cases, with a combination of the qualitative data sources, are utilised in regard to research question four.

The final part of this chapter is a synthesis of the interview results, bringing together the findings from the first and second interview rounds. This synthesis is done in regard to the first research question, since the answer to the research question can be seen to be built upon all the supporting research questions, and therefore all the previous sub-chapters.

4.1 Supplier information deficiencies in manufacturing organisations

During the first interview round, the interviewees from manufacturing companies were asked to identify information needs related to suppliers in their supply chains. This sub-chapter focuses on introducing the recognised information needs on a general level; therefore, it does not include verbatim quotes from the interviews.

Figure 16 introduces an overview of the recognised information needs in descending order. In the figure, the numbers tell the frequency of the mentions of the information need. One mention, on the other hand, refers to one mention of information need by one interviewee, meaning that multiple mentions of the same information need can be done by the same interviewee.

Figure 16. Overview of information needs from the first interview round.

Multiple interviewees emphasised environmental and social sustainability, mentioning that these subjects are increasingly important in the supply chain context. Out of the participating industries, environmental sustainability is highlighted in every single one, except the renewable energy and chemical industry. As environmental aspects have become more significant, it was mentioned that more detailed information about, for example, products, materials, emissions, and recyclability is required. Regarding environmental sustainability, multiple interviewees mentioned CO2 emissions, energy efficiency, and eco-friendly materials as significant factors that they want to have information about. One participating organisation also mentioned that, as they have themselves committed to different programs and agreements, such as the Paris Agreement or Science-Based Targets initiative (SBTi), they expect the suppliers to move towards similar policies too. This reflection was supported by a machinery manufacturing organisation's interviewee's comment about being informed about the whole supply chain, referring to the supplier's suppliers. However, the need to have visibility throughout the whole supply chain seemed to be a recurring theme in almost all of the information needs.

The need for information regarding any issues that the supplier might have related to environmental, social, and governance (ESG) related topics was emphasised. Another interviewee from industrial automation and engineering introduced that they also evaluate how the supplier addresses and solves their issues related to human rights or other ethical issues, and therefore, the need for a deeper understanding of social sustainability is highly needed. An organisation from the IT and technical engineering industry mentioned that having sufficient information and data about ESG-related topics would support more responsible and transparent decision-making in procurement and SPM.

Compliance, which was also among the highest priorities of supplier information needs, was mainly related to information about different certifications or credits that the supplier might have. For example, compliance was one of the most emphasised information needs in the field of renewable energy and chemicals, and an organisation from there mentioned that for them, it is important to verify whether the suppliers have industry-specific certifications, and from which organisations or regulators they have obtained them. Another insight came from the machinery manufacturing industry, stating that credit and basic compliance checks are essential during the onboarding process of new suppliers. In addition, sanction lists were mentioned by multiple organisations as an important information source for gaining knowledge about whether the supplying organisation or some of its responsible personnel are on a list.

Organisations operating in machinery manufacturing emphasised delivery reliability, but it was highlighted by mining and industrial equipment, and IT and technical engineering too. An interviewee from machinery manufacturing highlighted that in the case of active suppliers, information about reliability is essential to have. Information needs regarding reliability are mentioned, for example, to be delivery performance, timing, and amounts. However, another organisation introduced that reliability can be connected to, for example, the number of reclamations and other data existing in an ERP system, thereby indicating that delivery reliability can be seen as a combination that builds upon other information needs, such as quality.

Although quality and market trends were mentioned with the same frequency, quality was ranked higher in importance in almost all industries. Similarly to delivery reliability, quality-related information was mentioned to be important regarding existing and active suppliers. The mentioned quality information consisted of reclamations, quality issues, and incidents. Quality was also one of the types of information needs that was mentioned in a more quantitative context. However, it was multiple times mentioned that organisations would additionally like to gain information about how the suppliers solve or address quality-related issues. Market trends, however, were mentioned as a more emerging information need, that consists of, for example, supplier market data and how different market conditions affect certain suppliers either positively or negatively, but especially regarding possible delivery issues or risks. Market trends were mentioned to be, for example, market reports, manufacturing trends, trends regarding the end-users or suppliers, or trends existing in regard to other information needs, such as sustainability. Market data was mentioned as important, allowing competition to be created between suppliers. An important insight regarding market data was that the interviewees mention the absence of data multiple times in the context. For example, organisation from the industry of renewable energy and chemicals mentioned that supplier market data is extremely hard to acquire, or it does not even exist, since every company has different needs regarding it.

One of the less mentioned information needs is safety. However, the mentions can be explained by safety's relation to other information categories, such as social sustainability or compliance. Safety was especially emphasised in the food and beverage and power and energy industries, and it was mentioned to be continuously monitored throughout the whole supply chain. Safety however, had different definitions in different industries. For example, whereas IT and technical engineering mentioned especially information safety and security, industrial automation and engineering focused more on the employee's safety, therefore connecting the theme to social sustainability.

Supplier competence was mentioned through the supplier's capability to respond to the buyer's needs and through more traditional data, such as the size and capacity of the supplier. However, multiple interviewees mentioned supplier competence on a more general level, only mentioning the different things that a supplier can do. In addition, both supplier relationship information and contract information were considered less interesting. Contract information was mentioned to consist, for example, of information about the size and content of the order, or information about the supplier, such as turnover or the number of employees, or if there are already existing contracts with a certain supplier. For example, an interviewee from IT and technical engineering mentioned that it is important to obtain information about the linkage of the products they are purchasing. However, another interviewee mentioned that supplier relationship-related topics, such as cooperation and development, create new information needs.

An interesting insight was provided regarding supplier innovativeness. Some organisations mention supplier innovativeness as one of the more emergent information needs, which has been raised quite recently. That could indicate the smallest number of mentions in the interviews. However, especially organisations operating in mining and industrial equipment, and food and beverage sector mention supplier innovativeness as a highly important aspect. Information about what the suppliers can bring to the buying companies, as well as the supplier's ability to develop their technologies or other factors that can bring value to the buying organisations, was emphasised.

Figure 17 visualises the recognised information needs classified by the industry of the interviewees. A darker colour indicates a higher frequency of the same information need among interviewees from the same industry. In frequency, one mention therefore refers to a single mention of a certain interviewee, indicating that multiple mentions can be made by the same interviewee. As the industry of IT and technical engineering had six interviewees, in contrast to other industries, including only two interviewees, the mentions of the six interviewees were contextualised to compare the results in relation to the other industries. Therefore, while there were more interviewees from IT and technical engineering, the results were not manipulated by it.

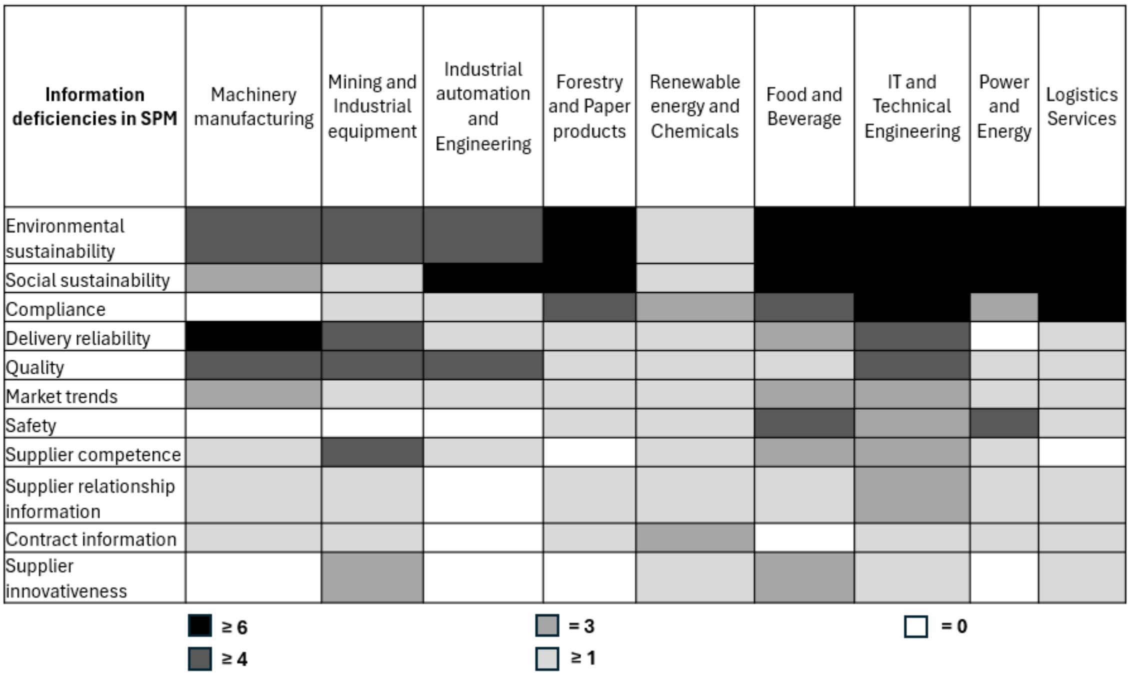

Figure 17. The weighing of information needs in different industries.

From figure 17 it can be interpreted that most of the participating industries value information related to sustainability the most. Quality and supplier compliance are also topics that are seen as important to have information about. Topics that were not brought up as much, such as supplier relationship information, supplier competence, safety, and contract information, might be something that the organisations see as self-evident and therefore have not been mentioned as much. For example, information about safety and quality was in the machinery manufacturing industry and IT and technical engineering mentioned to be more traditional ones and although significant, usually taken for granted. On the other hand, for example, quality was also mentioned as a traditional information need, but it remains one of the most emphasised information needs.

4.2 Capable supplier and supplier performance factors

In the second interview round, the interviewees were first asked to give their own definition of a capable supplier. The given definitions differed, mainly based on the industry and the role of the interviewee. However, all the definitions included performance factors, which had been introduced to the interviewees through the appendix table of the interview structure. The following figure 18 introduces an overview of the capability categories mentioned by the interviewees, in descending order. Since the scope of this thesis includes sustainability only on a general level, both social and environmental sustainability are now considered as one entity. Similarly to previous introductions, the number of mentions in the figure indicates the frequency of a certain capability factor, relating to a single mention of a certain aspect by any of the interviewees.

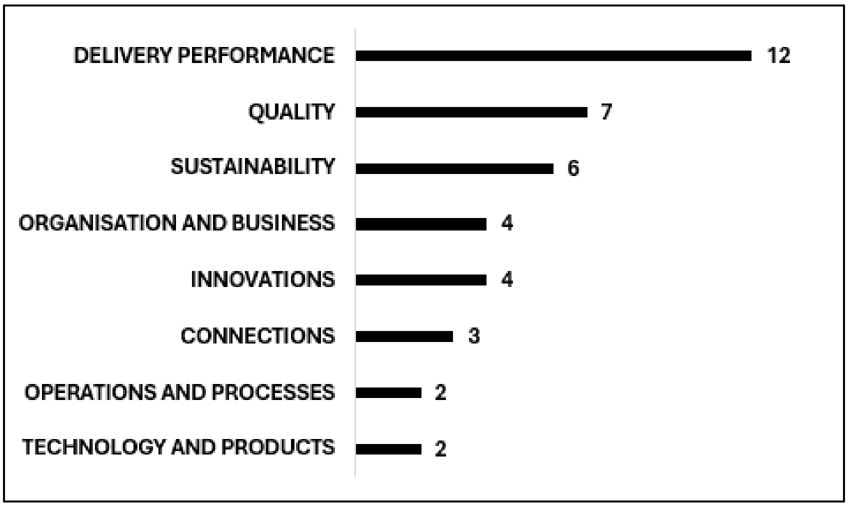

Figure 18. *Overview of emphasised supplier performance categories.*

From the overall answers of the interviewees, it can be seen that delivery and quality-related capabilities are valued. In addition, the following table 15 introduces the different supplier performance categories emphasised by each interviewee.

Table 15. *Interviewees' views on what a capable supplier expertise in.*

	A1	B1	C1	D1	E1	F1	G1	H1	I1	J1	K1	L1	M1	N1
Quality			x	x	x		x		x	x	x			
Delivery performance		x	x	x	x	x	x	x	x	x		x	x	x
Operations and processes				x						x				
Technology and products				x							x			
Organisation and business	x	x									x			x
Connections		x	x				x							
Sustainability				x				x			x	x	x	x
Innovations	x						x					x		x

As seen, overall operational capabilities seem to be emphasised the most. However, developmental aspects, such as sustainability, are definitely appreciated. The low number of mentions regarding operations and technical/product capabilities could be explained through the categories' similarities when comparing to, for example, quality or delivery, resulting in possible overlapping in the categories. On the other hand, relational capabilities may not be mentioned as frequently due to their subjective nature or the challenges associated with their measurement.

Interviewees who most emphasised the operational and technical capabilities were from industries of machinery and service, and industrial automation and engineering. On the other hand, an interviewee from the steel industry emphasised relational capabilities the most. Additionally, developmental capabilities were emphasised by interviewees from the food and beverages, and the forestry and paper industries.

Interestingly, all the interviewees except A1 and K1, emphasised capabilities related to the suppliers' delivery performance. However, the views might be affected by the interviewees' position in the organisation. On the other hand, these organisations mentioned that they mostly utilise local and quite specific suppliers that they have had a longer relationship with, indicating that perhaps capability factors related to deliveries are assumed without question, and not seen as value-adding capabilities. However, the interviewees from organisations with the largest overall supplier bases, such as M1, I1, and H1, did not mention that many capabilities, but rather focused on naming a few of the most important, with emphasis on delivery performance. This could, for example, result from the larger supplier bases and perhaps the difficulty of measuring every capability category from them.

Certain capabilities were therefore not clearly emphasised in certain industries. Some similarities can, however, be seen. For example, two interviewees from the forestry and paper industry seem to appreciate capabilities related to both quality and delivery performance, but the third interviewee, on the other hand, did not mention quality. Additionally, both interviewees from machinery and service mentioned delivery performance and sustainability. However, as there is variation in emphasised supplier capabilities in interviewees from the same industries, it can be interpreted that supplier capability comprises different interpretations and themes, based on the views of the respondent.

4.2.1 Technical and Operational Capabilities

From quality, different agreements, certifications, and consistency were emphasised. The importance of quality was emphasised by multiple organisations, such as A, B, and C, all of which mentioned quality as extremely important or even the most important performance category. In addition, N1 introduced the requirement of sufficient quality systems and reporting that the supplier must have towards the buying organisation. Interviewee M1 mentioned that quality is especially important since the majority of their product costs are derived from the materials provided by suppliers, indicating that quality is viewed more as a fundamental capability.

> *"Of course, if I look at the supplier, quality is definitely important to us. Since we are depending on suppliers and most of our product costs are coming from the materials and we try to optimise our inventories, we don't order the material too early to sit there and wait for when we need it. If we then find out something is wrong, that's usually too late and causes us a lot of challenges." ─ Interviewee M1*

Delivery performance, which was the most emphasised performance category, was connected to quality by multiple interviewees. For example, interviewee L1 mentioned that a capable supplier must be able to meet the buyer's expectations regarding delivery reliability and quality. In addition, according to I1, a capable supplier handles deliveries on time and of good quality. Interviewee N1 also emphasised delivery accuracy, referring to the buying organisation's changing needs. F1 complemented this by mentioning that it is essential to be able to trust that the supplier's deliveries meet the specifications and added that, for example, sustainability must be considered.

> *"A capable supplier is one who can manage their operations according to the customer's requirements, whether quantitative or qualitative, and deliver as agreed." ─ Interviewee N1*

> *"A great supplier in my opinion is a supplier who can deliver accordingly to the technical specifications as well as all the relevant KPIs, regarding for example sustainability." ─ Interviewee F1*

Interviewee J1 also mentioned delivery capability as one of the more traditional capability categories. Additionally, interviewee M2 agreed, as they see delivery reliability and quality as traditional but important capabilities. However, an occurring theme in addition to the topics related to the delivery contracts and technicalities, is the supplier's capability to be flexible and responsive. For example, C1 appreciates when the supplier is flexible towards the buying organisation. In addition, D1 discussed delivery flexibility and the differences between suppliers.

Operations and processes, and technology/product capabilities were mentioned the least. Regarding processes, the interviewees mentioned similar aspects as those related to quality. Different certificates, regulations and standards, such as a code of conduct, or industry specific EU regulations, are both required and appreciated. Interesting insight was also gained from interviewee I1, who mentioned that if international standards do not exist, they create their own to ensure a certain level of operations.

> *"Certifications are becoming increasingly important, certain standards and certifications are required just to be in business. For example, Organisation E might require a code of conduct, and if a supplier doesn't meet that, we can't do business with them, no matter how good they are, until it's fixed." ─ Interviewee E1*

> *"Certificates are important. In some subcategories, there are no international standards, so we create our own standards or define a minimum level that must be met. For example, we require traceability and alignment with our ESG agenda." ─ Interviewee I1*

In addition, traceability, flexibility, and visibility were also mentioned in the context of processes. Interviewee J1 mentioned that the supplier's production must be flexible and fast enough to respond quickly to changing or sudden needs. Interviewee N1 complemented the idea and mentioned that while functionality is important, key capabilities also include competence, traceability, and knowledge. Different certifications and laws are essential and therefore expected from the supplier, according to N1.

> *"Another important factor is how quickly they can implement product changes. We have frequent design changes, so the supplier must be able to adapt quickly." ─ Interviewee J1*

> *"Quality and functionality are probably the most important, maybe even the most important of all." ─ Interviewee A1*

Technology/product capabilities were mainly expressed through technology standards and functionality and also compared to quality-related aspects. For example, B1 mentioned that the most important capabilities are related to quality or technology. In addition, E1 explained that functional capabilities are not only appreciated but also mandatory.

4.2.2 Relational Capabilities

There appeared to be an intersection regarding relational capabilities, since the characteristics emphasised by the interviewees were not entirely distinct. However, as with the previous categories, adaptability surfaced multiple times when discussing organisational structure and capabilities. Interviewee N1 emphasised that the supplier must be agile and have the capability to adapt to the buying organisation's needs, making adaptability one of the clear requirements that they have for the supplier. In addition, I1 commented that the supplier must be responsive to the assignments given by the buyer, while also moving things forward themselves and maintaining the required service level.

> *"Some suppliers are very capable and willing to participate, while others are more reluctant, not necessarily because they have something to hide, but because it adds to their workload or they have a different organisational structure." — Interviewee I1*

Financial stability was also emphasised, as almost every interviewee mentioned its importance. As the focus was on qualitative measures, financial stability was discussed from a more proactive perspective, including therefore the risks associated with bankruptcy, as well as the operations done in cooperation with the supplier.

> *"We take a look, or we compare that our purchase is in line with the with the risk of suppliers economic situation." — Interviewee K1*

> *"Of course, price is one aspect, but before you can even talk about price, you need to consider the following: The supplier's financial situation, Supplier screening: are they close to bankruptcy, are they stable, what's their credit rating?" — Interviewee B1*

References and previous performance were also mentioned, for example, by interviewee A1. N1 approached the subject from a different perspective, including thoughts about reputation and the supplier's role in representing the buying organisation. N1 also added that the more the supplier has networks and relationships, the better it is. However, these capabilities are more difficult to prove, according to N1. Interviewee H1 mentioned brand strength and past performance as the main capability factors in this category.

> *"We definitely look at references, what the supplier has done before. If we're choosing a partner for an important project, it's crucial to know their track record and that they're a trustworthy brand." — Interviewee A1*

> *"Reputation and past performance also matter. A supplier must understand that when they work for us, they represent us, so reputation is important. Past performance affects whether we want to continue cooperation. If things start to slip, it impacts our decision-making." — Interviewee N1*

Capabilities related to connections, on the other hand, focused more on communication and collaboration. Interviewees such as D1, G1, K1, and C1 mentioned that the way the supplier communicates and collaborates with the buyer is important. Especially interviewee C1, who is a professional in the communication field, emphasised that interactions, effort, and the whole relationship with the supplier are crucial.

"The most important is definitely communication, how they respond and interact. A supplier might be technically excellent, but if communication is poor or difficult, even a high-quality supplier can be perceived as bad." — Interviewee C1

In addition, overall organisational structure, IT and system integration, were mentioned. Especially, system integration was mentioned to be a rising topic. For example, interviewee I1 mentioned that they have ambitious plans to integrate and synchronise their systems with those from suppliers. Interviewee N1, however, brought forward a more compelling viewpoint, stating that suppliers must use the same specific software that their organisation uses.

"*System integrations are absolutely essential. We have specific requirements that must be met before we sign contracts, certain systems must be used." — Interviewee N1*

On the other hand, interviewee G1 mentioned that while connections and organisational structure are important, their significance depends highly on the criticality of the material or service that the supplier is providing. Additionally, H1 added that interpersonal trust is also significant, although its importance similarly depends on what the supplier is providing and how critical it is.

4.2.3 Developmental Capabilities

As introduced, sustainability was ranked as third-mentioned capability category. Regarding sustainability, numerous certificates, legislations, and standards were mentioned, such as The Paris Agreement, code of conduct, SBTi, ethical guidelines, and CO2 emissions. These standards were, by multiple interviewees, mentioned as the base expectations, rather than capability aspects. In addition, it was mentioned by multiple interviewees that usually sustainability is something that can immediately break the cooperation between the organisations, if it is not taken care of accordingly. For example, interviewee A1 emphasised that regardless of what side of procurement the supplier is, code of conduct and ethical guidelines must always be signed.

"Basically, it's a baseline requirement. If a supplier doesn't meet certain standards, they can't be selected. They wouldn't even be considered our supplier if they lacked competence in sustainability, for example." — Interviewee C1

"Anything related to environmental, social, or ethical principles, like human rights are showstoppers. They're asked about first. If there are violations or no code of conduct, we don't proceed." — Interviewee D1

Interviewee B1 however, discussed interesting aspects of sustainability, mentioning that some factors are assumed to be in order as, for example, waste management, while some others, such as the CO2 footprint, come up in further discussions with their suppliers. B1 also mentioned the positive progress in actions related to sustainability.

> *"For example, waste management, emissions, and pollution, we assume those are already in order. Ecological materials and carbon footprint are part of a newer wave that's emerged in the past five years. These topics clearly come up more in discussions and communication with suppliers. It's no longer just talk, which I really appreciate. Talk is cheap, but action is what counts." ─ Interviewee B1*

Additionally, multiple companies mentioned that safety is highly important, and that it must be ensured throughout the entire supply chain, therefore referring to the suppliers' suppliers. Employee well-being and ethical subjects are expected to be addressed throughout the entire value chain, and the cooperation can be stopped if all parties involved are not compliant.

> *"Safety is our number one priority, along with employee well-being and working conditions. Social sustainability is a central aspect." ─ Interviewee N1*

> *"The whole chain must be compliant with regulations around the world, for example, that there is no unethical labour in use and that we have correct welfare for different employees. And we need to ensure that all of this happens in the whole value chain." ─ Interviewee F1*

Regarding sustainability, organisations also seemed to appreciate the supplier's capabilities to develop their operations and improve their ESG-related factors. This, on the other hand, can be connected to the supplier's capabilities in innovating.

> *"Innovation, as mentioned earlier, we mostly expect innovation in terms of sustainability. Can the supplier switch to greener energy? Can they replace fossil-based components with more sustainable alternatives?" ─ Interviewee G1*

However, multiple interviewees, such as B1, C1, and I1 mentioned that innovation usually goes both ways, indicating that the supplier and buyer should both be able to innovate, and therefore improve each other's business and operations. However, interviewee E1 brought up an interesting thought, that if the industry has been existing for quite a long time and the relationships with suppliers have lasted for a long time, is there actually anything new that the suppliers can bring to the buyers. However, they mentioned that there is always the possibility that the supplier might surprise them with new innovations. On the other hand, interviewee D1 and G1 had contradicting thoughts, since they mentioned that actually the suppliers that are ahead or better, are the ones you should be paying for, and that the supplier should have growth goals and targets that are aligned with the ones the buyer has.

> *"We want our suppliers to help us to succeed. In that case it is good if there is innovation every now and then in the areas that they are supplying us. And also, what can we improve, what kind of changes we could do, and we hope that our suppliers will really help us improve our working too. Or help us to develop our own work and processes. In that sense, innovation is important." ─ Interviewee K1*

Some buyers might expect the supplier to act regarding the development of their relationship with the buyer. For example, as interviewee N1 mentioned, suppliers with the most developed and modern technology are preferred, interviewee L1 complemented this by adding that they appreciate a supplier that additionally strives to improve their collaboration. Innovations can also be achieved in other ways. For example, interviewee G1 suggested that innovation could exist in different parts of the supply chain, such as transportation, the efficiency of extracting certain minerals, or the processing of these minerals.

4.3 Current challenges in Supplier Performance Management in manufacturing organisations

The interviewees were asked to introduce the challenges that they currently have in supplier assessment or SPM. The main themes of the issues regarded either data-related issues, technology or systems, or challenges related to human resources, such as manual work or root issue tracking. Figure 19 gives an overview of the mentioned challenges and their frequencies, which indicate the overall amount of mentions regarding a certain challenge. However, to gain a comprehensive understanding of the difficulties related to SPM, the challenges are introduced through the performance categorisation introduced previously.

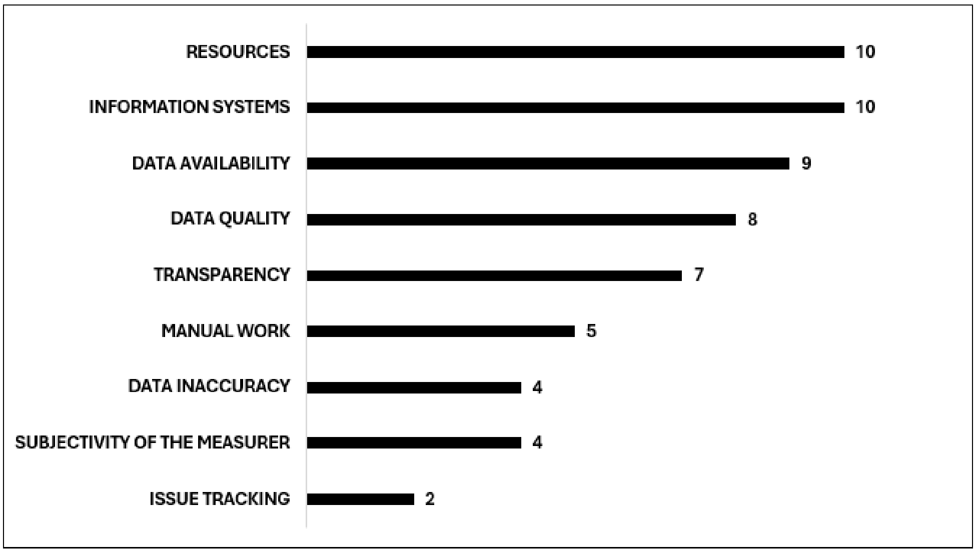

Figure 19. Overview of mentioned challenges.

Similarities regarding interviewees from the same industries can be found. Interviewees A1 and H1 from machinery and service both mentioned IS or lack of it as a difficulty. Similarly, interviewees C1 and I1 from forestry and paper emphasised the lack of resources as a difficulty. Additionally, interviewee N1 from the same industry mentioned manual work, which can also be connected to the challenges regarding resources, since if the level of manual work is high, more resources are utilised there. Interviewees from the industry of industrial automation and engineering both subjectivity of measurement and data accuracy as challenges, which can also be as interconnected, since data inaccuracy might be the result of subjective measurement. Other than the mentioned, similarities between interviewees from same industries were not recognised.

Differences between different industries were not necessarily recognised, since interviewees from the same industries seemed, in most cases, to emphasise different things, indicating the larger scale of issues existing in every industry. However, slight differences could be observed, as for example interviewee L1 from food and beverages mentioned that while data is available in large amounts, they simply have challenges regarding resources to utilise all the data, while on the other hand, for example, interviewee G1 from the chemical industry emphasised more the challenges related to data itself, mentioning data availability too.

Current challenges related to quality capabilities and quality management were mostly related to manual work and the utilisation of human resources. Quality data tends to be unstructured and come in large volumes, resulting in inconsistency. Interviewees D1 and K1 both mentioned that quality might be perceived subjectively, and therefore, challenges related to it might be raised, since everyone might see things a bit differently.

"Then for claim handling there is always a challenge that what is the correct risk level for a claim for example" ─ Interviewee D1

"The problems are related to human beings because sometimes people think that, OK, this is not perhaps as good quality as we would like to have it, but we don't mind complaining to the supplier, and they are not writing down the problem into the tool, because it's extra work that needs to be done. " ─ Interviewee K1

This, according to interviewee K1, has sometimes led to situations where they are unsure about the actual quality of the product. Relatively, interviewee F1 mentioned that they are currently working to make quality data more accurate. In addition, interviewee G1 noted that in some situations they have simply assumed that slight deviations in quality data are acceptable. G1 also mentioned the manual work in quality management.

Similar challenges existed regarding operational and process-related data. However, while unstructured data and manual work were mentioned, interviewee J1 mentioned that the bigger issue is the difference between the view of the buyer and the supplier, which is a result of unclear metrics.

"Well, the metrics could be clearer. When we discuss them with suppliers, they often have a different view. It takes effort to agree on the numbers" ─ Interviewee J1

Additionally, the lack of centralised systems was raised. Because automation or integrated solutions are not used, it is difficult or impossible to predict something or even make changes quickly. This could create possible bottlenecks regarding information flow too.

“We don’t really have a formal system. It’s more conversational and reactive if someone suddenly stops performing or doing their tasks, we respond to that." ─ Interviewee A1

Challenges in delivery management, performance, and delivery information, on the other hand, seemed to include issues related to data reliability, accuracy, and the unstructured nature of it. Interviewee D1 mentioned that data accuracy is always a challenge, so they try to align it, for example, on a monthly basis to really recognise what has been done correctly, and for example, what deliveries have been late. Additionally, as unstructured data passes through multiple people and systems, changes to it might not be recorded accordingly, resulting in unreliable data.

“When tracking delivery reliability, the delivery term affects when goods are considered received. Our systems might apply a default lead time for it, but whether

> *that’s accurate is another matter. So, when you’re measuring delivery reliability, it can get tricky." ─ Interviewee H1*

Regarding organisational structure and relational information, the interviewees emphasised that data related to these capabilities is usually difficult to collect, since they might rely on, for example, subjective experiences and manual work. Interviewee G1 noted that a regular employee might not be able to find the data, resulting in a lack of visibility. Additionally, G1 discussed transparency challenges, as they may not always be able to obtain information regarding the entire supply chain, rather than only the direct supplier.

> *"We might check annual review of management or the management review that is done usually once or twice a year. But then that's subjective of course and very much depending on the supplier." ─ Interviewee D1*

> *"For example, with sanctions or restrictions, we can ask our direct supplier, but how can we be sure there’s nothing problematic further upstream? Transparency into the full supply chain would be amazing." ─ Interviewee G1*

Another challenge was the lack of systems, which interviewee G1 addressed by mentioning that they have not been able to integrate their systems, accordingly, resulting in questions regarding efficiency and the use of different data sources. However, I1 mentioned that a line has to be drawn somewhere regarding the systems, since they cannot adapt to every supplier, since resources to do it simply do not exist.

> *"We don’t have the resources; we’d need to hire several data scientists just to input and manage the data." ─ Interviewee I1*

Developmental capabilities included challenges similar to the previously introduced, since a large number of suppliers bring with them a large amount of unstructured data, which might even be communicated in an informal manner.

> *"Basically, what comes to sustainability is that information is pretty much coming from our suppliers and because we have quite a lot of suppliers, we can't meet them all during a year. So, we don't have time to invest to the sustainability topics they are having and seeing." ─ Interviewee K1*

> *“Another challenge, also related to resources, is tracking development areas and continuous improvement. Ensuring that suppliers actually improve based on evaluation results, and if they don’t, being able to make agile decisions about the collaboration, that all comes down to how well we can manage our supplier base and develop those relationships." ─ Interviewee L1*

Therefore, in addition to the lack of resources, visibility may also be insufficient. C1, for example, mentioned that because of the number of suppliers they have, it is very hard to track every one of them. Regarding sustainability, F1 also mentioned that they lack the resources to examine the entire supply chain. Additionally, L1 mentioned that resources prevent the organisation from assessing as many suppliers as they would like.

4.4 Qualitative data in Supplier Performance Management

The interviewees were asked to recognise qualitative data sources and data types in the interview. The mentions of qualitative data were either those that the organisation currently utilises, or those that the interviewees see potential in. Overall, the most mentioned qualitative data sources consist of different certifications, documents, reports, or more informal sources, such as meetings or feedback. Figure 20, as an overview, introduces the mentioned different qualitative data types. The number in every data source refers to the total number of mentions across all interviews. In the analysis, reports refer primarily to documents done by the buying organisation, such as monthly reporting or their own guidelines, indicating contrast to the supplier's documents, which are primarily provided by the supplier, therefore including, for example, their own certificates or statements. Additionally, the difference between conversations and meetings comes from the formality of the event, meaning that conversations often involve more informal encounters.

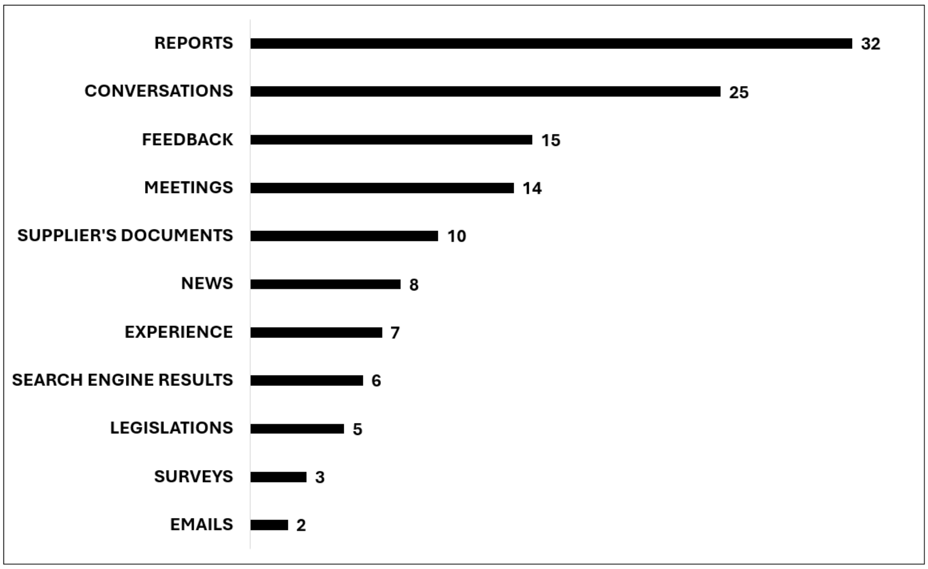

Figure 20. Overview of mentioned qualitative data sources.

No significant similarities or differences were found regarding the interviewees' industries. However, almost all of the mentions regarding search engines were made by the interviewees from the machinery and service industry. Additionally, using experiences, such as site visits, were mentioned most by the industrial automation and engineering industry. Also, for example, supplier's documents were highly emphasised by the interviewee from the steel industry, but other industries did not mention them as much. More significant dependencies, however, were not found. Therefore, it can be stated that the mentioned data sources might not depend on the industry, but rather on the experience and position of the interviewee. The following sub-chapters provide a more thorough analysis of the interview results. The same capability categorisation is used as in the supplier capability analysis.

4.4.1 Technical and Operational Capabilities

Regarding quality, the interviewees mentioned multiple different data sources that are based on human experience. For example, interviewee B1 mentioned that they tend to have conversations with colleagues who have previously worked with a certain supplier to gain information about their state of quality. In addition, interviewee I1 mentioned that they regularly interview teams from production to get a concrete insight into how things have been done. On the other hand, interviewees J1 and M1 mentioned end customers as a source of data, referring to customer feedback and complaints.

> *"For quality, we interview production teams to see how things have gone." ─ Interviewee I1*

> *"Organisation D regularly sends customer satisfaction surveys. I assume we have good tools for that." ─ Interviewee D1*

Based on the feedback or complaints, the buying organisation creates quality claims, which additionally can be used as a data source, as for example interviewee I1 stated. Interviewee M1 also introduced how they have teams that visit the supplier's site. These sourcing teams were said to have quality personnel who evaluate the supplier's operations. The operations and processes are evaluated based on the different agreements or contracts that the buyer has with the supplier. As interviewee A1 mentioned, all quality requirements are defined in the contracts. Different standards and certifications, such as the Certificate of Analysis (COA) and ISO 9001 are mentioned as mandatory, as interviewee E1 stated, or highly encouraged and valued, as interviewee G1 indicated. These are collected from the supplier through, for example, different questionnaires.

> *"For raw materials, they must provide a technical data sheet, a material safety data sheet, and respond to our raw material quality questionnaire. They also need to provide a REACH certificate, which is mandatory in Europe and often required globally." ─ Interviewee G1*

> *"We always want to receive a COA (Certificate of Analysis), which reflects the agreed specifications outlined in our technical datasheet. If we encounter a quality issue and discover that the material was out of spec, we file a claim and demand compensation." ─ Interviewee I1*

Data sources mentioned in the context of process capabilities, on the other hand, seemed to focus more on qualitative data acquired from meetings or live conversations between professionals. Discussions during live and remote meetings provide subjective experiences that can support or present different views to the reports the supplier provides.

> *"We also have a lot of internal discussions. Since we're a global group with many factories and contacts, we talk a lot with other sites." ─ Interviewee J1*

For example, interviewee D1 mentioned that during their weekly meetings or business reviews, their suppliers present reports that show basic metrics and the current state of operations. Interviewee J1 also mentioned the importance of weekly monitoring and meetings. Additionally, E1 mentioned that they do the same thing on a monthly basis. All in all, most of the data is gathered via human contact.

> *"We might ask procurement about invoicing and order handling, or someone from manufacturing about service quality and safety compliance." ─ Interviewee G1*

In a similar manner, interviewees A1, C1, J1, and M1 mentioned that regarding the supplier's delivery performance, they usually rely on their experience or communication between the buyer and the supplier. These conversations can provide information about supplier's references, certifications, or operational forecasts, as interviewees M1 and A1 mentioned. B1 also mentioned informal conversations, which enable personal relationships from which, for example, early warnings can be acquired. Additionally, internal inquiries and meetings are emphasised.

> "*We have meetings with our most important suppliers. Depending on the type of the supplier, we might have meetings on a monthly basis, or we might have meetings only once a year." ─ Interviewee K1*

> *"We also do internal inquiries, sending emails, asking how things have gone. Within our corporate group, several companies use the same suppliers." ─ Interviewee C1*

More structured data sources, however, included different legislations, technical data sheets, or similar certifications as mentioned previously. Especially legal documents and regional legislations were emphasised, as they can be easily used to evaluate the supplier. For example, interviewee L1 mentioned that the buyer can quickly refer to a certain legislation when assessing the supplier's deliveries.

4.4.2 Relational Capabilities

Data regarding suppliers' organisational and relational capabilities is collected in similar ways. Meetings, conversations, and feedback are used to monitor cooperation, communication, and service.

> *"I mostly monitor how the cooperation with the supplier is going and react accordingly. Right now, it's done through weekly meetings." ― Interviewee H1*

Interviewee I1 mentioned that other professionals from procurement can be utilised to gather information about, for example, organisational performance and financial information. Additionally, J1 mentioned that they conduct extensive internal research on the supplier by consulting with other colleagues or by even asking other companies. An interesting insight came from interviewee B1, who mentioned informal conversations that happen in different social settings, and how this technique helps the participants negotiate information regarding, for example, initial assessment of potential risks or uncertainties. Additionally, B1 mentioned that personal conduct and the overall presentation of the supplier greatly affect the appearance of trustworthiness.

> *"That kind of negotiation tactic, finding a common target is very important in strategic procurement. It's also how you get warnings like "raw materials are running low" or "prices are about to rise." ― Interviewee B1*

However, according to the interviewees, a lot of organisational data is also collected through the buyer's independent searches. For example, interviewees A1 and B1 mentioned search engines and the supplier's public information as sources of data. Additionally, B1 mentioned that they tend to check background information regarding ownership structures and board members. I1 complemented this by mentioning reports that they try to search for. However, interviewee G1 stated that this information is rather acquired by asking the supplier and engaging in conversations with them. This type of data regarding relational capabilities is something that interviewee J1 wishes there were more of.

> *"If there were press releases or other updates about suppliers, we could get a better sense of where they're heading. A few times now, a supplier has gone bankrupt unexpectedly, and that causes a real scramble." ― Interviewee J1*

Emails and attachments sent by email were mentioned by interviewee B1 as a data source, especially regarding suppliers whose information might not be publicly available.

Furthermore, interviewee M1 added media publications and news reports as data sources to gain information about specific relations. Questionnaires or surveys are used to acquire information related to the mentioned sources. However, C1 stated that tracking communications and relations systemically is too expensive, and therefore, it is mainly done through personal observation and interactions.

4.4.3 Developmental Capabilities

Different certifications and legislations were mentioned as highly important sources of information in sustainability-related subjects. Interviewee D1 mentioned that, for example, a code of conduct is expected, and if it is not available, they do not proceed with the relationship with the supplier. Interviewees E1 and L1 also mentioned the use of codes of conduct, Paris Agreement files, and for example Forest Stewardship Council documents as important sources of data. Additionally, ISO certificates and other ESG documents were mentioned. However, I1 mentioned that some suppliers may not have the resources for official certifications, in which case the buying organisation itself conducts the needed audits. H1 also mentioned the use of their own internal data and reports.

> *"We have a sustainability questionnaire. It includes questions about environmental and sustainability practices, human rights, waste management, water treatment, working conditions, and whether they have any sustainability processes or principles." ─ Interviewee L1*

> *"ESG risk is also based on supplier capabilities, what certifications or evidence they can provide. But when there are no certificates or public proof to immediately convince us, we conduct audits." ─ Interviewee I1*

Furthermore, sustainability subjects emerge during meetings and discussions with the suppliers. Interviewee D1 mentioned that they continuously have discussions related to these subjects with the suppliers. B1 also mentioned that the use of ecological materials and CO_2 footprint usually emerges during discussions with the supplier. In addition, A1 indicated that conversations and texts used in communication with the supplier can be used to identify clues about unethical behaviour. E1 supported this by broadening the scope of the supplier conversations into the entire supply chain.

> *"We're always interested in where suppliers source their raw materials, if they're sourcing from questionable places, we'd want to know. This often comes up in open conversations, but still." ─ Interviewee E1*

K1 explained that they have a tradition of organising supplier days, in which the idea is to have conversations on whatever topics are important at the moment. These larger meetings are used to acquire information about the chosen topics, but also to gain anonymous feedback from the suppliers. On the contrary, M1 mentioned that these subjects are usually covered in one-on-one discussions with a specific supplier.

> *"Regarding environmental topics, we take care that our suppliers understand what is valuable to us and what we want that they are focusing on too. It can be safeness, or it can be environmental aspects. And in those meetings, we always want to get input from our suppliers that how do they see us and what is important that we should focus on in the future. So that kind of feedback we are evaluating or receiving from them." — Interviewee K1*

Additionally, experiences and, for example, site visits were mentioned as data sources by, for example, interviewees F1 and C1. Specifically, C1 emphasised that external observations can be used to verify the supplier's current state and to really see how, for example, the employees are doing in the company. H1 supported the idea by mentioning that they investigate, for example, employee turnover. Moreover, other external or third-party sources were introduced too. Interviewee G1 mentioned that a third-party source is essential, since it provides information that the organisation would not be able to collect itself. Supplier websites or search engine results are also used to verify sustainability information, as E1 introduced.

As demonstrated in prior analysis, innovation-related capabilities are seen more as emerging subjects, and therefore, data sources were not mentioned as much. However, especially search engine results, news reports, and media publications were mentioned. Interviewee J1 mentioned, that they would like to see press releases to gain a better idea about the supplier's operations. L1 mentioned that they constantly follow news reports to gain information about possible negative subjects, or potential developments or new technologies.

> *"If a supplier ends up in the news, that's usually a sign that things are going badly. But we also monitor the market and news for changes like mergers or other developments in the supplier landscape." — Interviewee L1*

Interviewee D1 however, brought up conferences and industrial-specific trade shows. They mentioned that some personnel attend these meetings, while for example, technical personnel focus more on publications done in their field of profession. As did D1, but also F1 mentioned initial meetings, where they get information about different projects that the suppliers might have planned or in place, for example, regarding sustainability.

4.5 Natural Language Processing potential in Supplier Performance Management in manufacturing organisations

All organisations except organisations F, K, and N mentioned the use of NLP applications, such as LLMs in their organisation. However, there were differences regarding the level of use: some organisations used them widely across the whole organisation, while others were only piloting the solutions in some departments. Not only that, but some organisations had their own internal solutions in use, while the rest, on the other hand, utilised third-party solutions with their own licenses. Table 16 gives an overview of the organisations' current situation regarding the use of NLP applications.

As seen from the introduced classification, third-party licenses are the most popular solution for utilising AI and NLP. While some examples of internal systems exist, the lack of them could indicate to, for example, the high need for resources, that the internal implementations require. However, it could also be said that also in the organisations that did not mention the use of NLP, it is possible that certain individuals do use NLP or LLMs in some way, but not in a structured manner. Regarding the interview results, the current state of NLP in the organisations did not seem to have a remarkable effect.

Table 16. Current state of NLP applications in manufacturing organisations.

Organisation ID	Current state of NLP
A	3rd party licenses
B	3rd party licenses
C	Internal closed system
D	Internal closed system
E	Piloting
F	Not using yet
G	3rd party licenses, Scouting solutions
H	3rd party licenses, Internal closed system
I	3rd party licenses
J	One unit uses 3rd party licenses, Scouting solutions
K	Not using yet
L	3rd party licenses
M	3rd party licenses
N	Not using yet

The following figure 21, however, gives an overview of the most frequently mentioned NLP technologies that the interviewees emphasised. It can be seen that most mentioned use cases involve extracting information from various sources, comparing different values, and summarising natural language documents. The numbers indicate the overall amount of mentions regarding a certain technology, therefore giving information about what was mentioned the most and what the least.

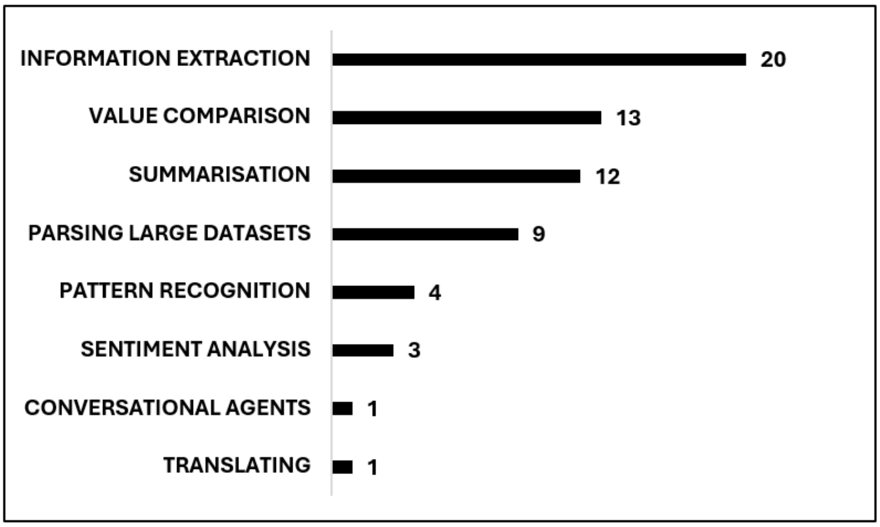

Figure 21. Overview of mentioned NLP potential.

Additionally, figure 22 gives an overview of the use cases of NLP. The number in the categories indicate to the overall mentions of a certain use case in a certain category. Regarding the use case of operations and processes, especially interviewees from forestry and paper industry seemed to be interested in them. Additionally, sustainability was a popular category in the industry. On the other hand, delivery performance and quality were emphasised by interviewees from industrial automation and engineering. The interviewee from the industry of chemicals was also interested in possibilities regarding quality capabilities. Regarding the other use cases from the capability categories, certain patterns or dependencies could not be recognised.

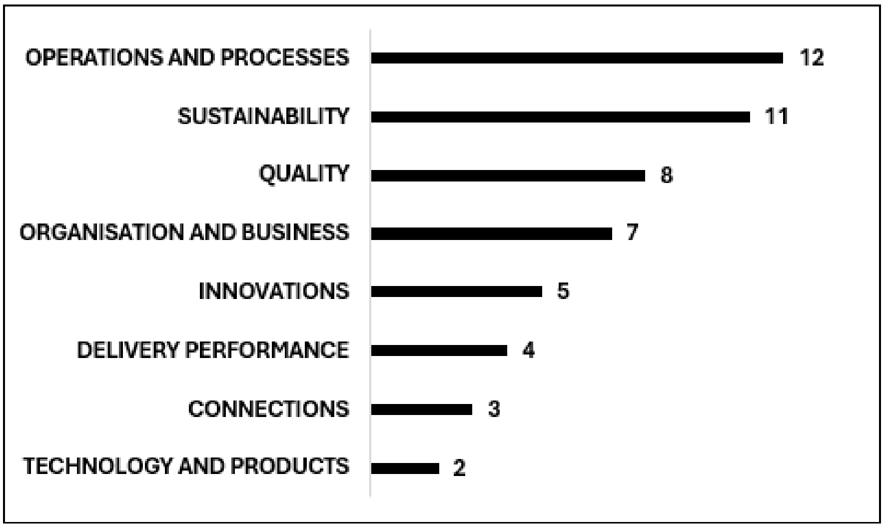

Figure 22. Overview of mentioned NLP use cases.

Out of all the capability categories, most use cases were recognised in operations and processes, sustainability, and quality. In contrast, the least use cases were recognised in delivery performance, relations and connections, and technology and products. The category of technology and products can be explained by the category's overlapping with the other operational categories. Although organisational structure and connections are presented in the figure as two different categories, the use cases existing in them can well be seen to be connected. It is also important to note that use cases related to risks and risk management were recognised numerous times, but as risks are outside of the scope of this thesis, these use cases were put under other use cases they were related to, if possible. The mentioned use cases and potential will be further introduced in the following sub-chapters.

4.5.1 Technical and Operational Capabilities

As data regarding quality capabilities consists largely of different certifications and standards, NLP can be potentially used to search, screen, and analyse them from various sources. Interviewee B1 addressed that a lot of the work related to the mentioned is currently done manually. Therefore, they suggested that an NLP algorithm could screen either supplier's documents or websites to gain information about their certifications and standards or analyse other sites to compare the information and values with the supplier's operations. This could be potentially combined to quality issues, by tracking said problems and linking them to collected feedback and production issues. Therefore, tracking quality deviations could be enhanced. Interviewee J1 also mentioned that in quality management, AI algorithms could be used to identify specific patterns and therefore predict possible quality issues.

> *"We have a system where we store our specifications and the supplier's technical data sheets. Each delivery comes with a Certificate of Analysis showing the tank's values. Ideally, an AI could read all of these and flag if, for example, Tuesday's tank was slightly outside the specified range." — Interviewee G1*
>
> *"For quality, definitely, tracking quality deviations, and if there's textual feedback or collected data, AI could be great for summarising." — Interviewee C1*

As interviewee C1 brought up summarising, additionally NLP could be used to create reports or summaries based on quality data sources. Interviewee E1 suggested that AI could generate summarised reports, enabling more visible supplier capabilities. Interviewee K1 mentioned that as they must always check the materials that the supplier provides AI could easily read and analyse them and compare them to, for example, certificates or specifications stated in the contract. J1 also added that they know of a supplier that uses AI to assess whether the buying organisation's quality specifications or limits are appropriate.

Interviewee A1 said that NLP definitely has potential in compliance and analysing how well suppliers follow certain regulations. AI could analyse, for example, different lists and suggest improvements if needed. In like manner to quality, NLP algorithms can screen different sources and create an overview of certifications or legislation related to operations. C1 also suggested that AI could verify if a specific certificate is outdated and suggest a more comprehensive or current one.

> *"If I take compliance. AI could check what is the local legislation and what the other regulations would the supplier need to comply with. And then sort of give information to us on what it would be." — Interviewee D1*

NLP algorithms could additionally analyse supplier emails regarding operations and therefore enable, for example, more automated and on-time tracking. J1 mentioned that information regarding changes related to major suppliers, such as product discontinuation or relocation, could be acquired faster with AI. A significant number of resources and manual work are allocated towards SCM and SPM, creating opportunities for automation.

> *"AI could automate certain tasks. We use a lot of human resources to manage and operate our supply chains, and I'm sure AI could model things like how much to order from where and what our inventory levels are. If linked to our ERP systems, it could automate many tasks." — Interviewee I1*

Interviewee I1 also mentioned that supplier teams tend to be overwhelmed with basic tasks, indicating that routine work should be automated to some extent. Similarly, G1 mentioned that regarding delivery data, AI could provide an overview or summary consisting of all aspects related to the subject, helping professionals give up basic tasks. K1 supported this view by mentioning that by analysing overall delivery data, AI could generate simple tables, visualisations, or summaries, from which professionals could easily identify any issues regarding deliveries.

> *"It would also include the ability to analyse our consumption of a specific material, for example, how the price has developed, what alternatives exist? Have there been quality issues? So that you'd get a kind of comprehensive summary or overview of things. It could well be that for someone, quality hasn't been an issue, so it doesn't show up as a risk, but for someone else it might be like, hey, compared to other suppliers in the same field, this one has three times more issues." — Interviewee G1*

Furthermore, by analysing different public sources, NLP algorithms could compare suppliers and, for example, different events to gain information about factors that might affect deliveries. F1 suggested that, for example, by screening news articles and connecting subjects to each other, the buyers might gain important information about possible risks.

> *"I think it would help with analytics and the performance of these indicators. For example, AI could identify that, hey, this supplier has been late the past four years, I don't know, in June or July. So should you check what is actually happening in June and July?" — Interviewee F1*

Overall, AI’s capabilities to screen and analyse content, and create indications or identify patterns are important, and multiple interviewees expressed this potential. Regarding operational and technical capabilities, AI could also work as an assistant, freeing personnel to focus on other tasks.

4.5.2 Relational Capabilities

As with previously introduced capabilities, AI could be used to create lists or summaries based on formal or informal documents gathered from different sources. Similarly, meetings and meeting transcripts can be summarised or analysed by NLP algorithms. Interviewee A1 also indicated that AI can support employees in remembering important parts of certain documents or of, for example, meeting transcripts. K1 noted that NLP algorithms could create meeting memos and extract specific or important topics from of them. I1 mentioned that they have utilised AI by asking it for help in finding sources from which organisational data could be acquired.

> *"It could help a lot with things like meeting notes, it records and drafts them, and then you just go through them. That saves a lot of time. Or by using prompts to list things. AI is great for helping you remember everything important." — Interviewee A1*

Multiple interviewees, such as C1 and D1, mentioned that NLP algorithms could potentially screen multiple sources and compare different suppliers based on them. For example, C1 suggested that real value could be created if the AI could give suggestions based on, for example, the supplier’s financial situation, if they should, for instance, demand more from the supplier.

> *“Yes, that kind of text processing could go through various data sources." — Interviewee D1*

> *"This technology has the capability to connect all the dots, it can scan what is happening around a certain topic and based on the parameters you have set up on your business, it could connect all the dots and suggest business-related initiatives that could be beneficial." — Interviewee F1*

NLP algorithms could have potential in screening informal sources, such as emails. Interviewee F1 mentioned the possibility of analysing data and sources that have not been classified or manipulated. C1 also indicated that a great way to utilise NLP would be to collect data on how the supplier organisation communicates. M1 introduced that they have tried to utilise AI as a search engine, to look into suppliers or give suggestions about potential suppliers. However, M1 added that it could be really difficult to analyse communications, since they consist of subjective human interactions.

> *"You could record all meetings and analyse whether the supplier uses softer language with us than with other customers, but maybe not worth it." ─ Interviewee M1*

C1 also raised concerns regarding relational data, since the AI should be capable of creating quite complex analyses and comparisons. If the NLP algorithm is only able to give short statements about, for example, the supplier's financial situation, without providing something that human personnel might not themselves see, it would perhaps not be that useful.

4.5.3 Developmental Capabilities

Sustainability data exists in large amounts, and NLP algorithms could analyse it effectively and faster than human personnel. Interviewee D1 mentioned that AI could take in a lot of information, such as certificates and sustainability reports, process it, and create visualisations or summarisations that the professionals could easily review. Multiple interviewees suggested that AI could screen and analyse different sources of information and compare those to documents provided by suppliers or to, for example, suppliers' websites. Especially checking for validity is something that the interviewees mentioned. For example, interviewee I1 stated that NLP algorithms could be utilised as support tools to assess the documents provided by suppliers and analyse whether the information is valid or not.

> *"It could scan public sources, like science-based targets, and identify which companies are part of the program. It could also check sustainability reports and tell us whether a supplier aligns with the Paris Agreement. If they're not on the SBTi list, AI could check their reports. If they're not aligned, we'd know. It could even tell us how far off they are and what they'd need to do to comply, especially if they don't want to join the SBTi but want to improve their practices." ─ Interviewee E1*

I1 mentioned that sometimes the supplier documents are written in a language that they do not understand, and NLP algorithms could be utilised as translators, freeing up the personnel to other tasks. Furthermore, based on the analysed materials, AI could pinpoint the buyers in the right direction. Interviewee D1 brought up that the algorithms could highlight topics or parts of a document, that the organisation should shift focus into or examine more profoundly. Interviewee E1 also mentioned that AI could emphasise something that might be a sustainability risk, for example if the suppliers are sourcing materials from questionable sources.

> *"Let's say in subcontracting, perhaps occupational health and safety assaults are higher risk that we will need to assess more. Or is it a consultant that is providing software to us, then it is a different kind of risk that they would need to highlight." — Interviewee D1*

D1 also mentioned that the algorithms could highlight and categorise risks based on what the buyer wants to know more about, whether it is locations or specific businesses. G1 also mentioned that it would be useful if all the information were located in one place, considering the case that alerts created by third-party software or adverse media alerts could be combined.

Regarding innovations, managing large volumes of unstructured data and screening publications or reports was mentioned. C1 suggested that NLP algorithms could analyse public sources to see if a certain supplier has been recently innovating. D1 also supported this by suggesting that AI could search for different suppliers based on certain keywords or names of technologies that the buying company has used in the prompt. Interviewee C1 also highlighted that a supplier company might have been innovative in the past but has since become comfortable as it has found reliable customers. Therefore, future potential would be important to analyse. L1 also mentioned that if an algorithm could analyse sources containing information about innovations, the buyers would not have to wait for the supplier’s communication about it.

> *"And of course, it can track mergers or acquisitions involving suppliers without waiting for them to inform us." — Interviewee L1*

Additionally, related to both sustainability and innovation, it was mentioned that NLP algorithms could support and guide the buyer’s long-term strategies. C1 mentioned that for all developmental capabilities, AI could enhance the strategies and help the managers significantly since, for example, tracking a large number of suppliers simultaneously is challenging. C1 also continued that, especially when managing large volumes of data, NLP algorithms have great potential.

4.6 Synthesis of the interviews' results

The interviews from the first round provided a comprehensive overview of the different information needs currently existing in SPM. While the information needs varied, based on, for example, the industries of the organisations, the most mentioned were sustainability, quality, reliability, and compliance. The least mentioned categories were supplier innovativeness, safety, and information related to supplier relationships and contracts.

The information needs were connected to the capability categories of SPM. From the more precise supplier capability categories, capabilities related to the suppliers' delivery, quality, and sustainability were emphasised. Relational, organisational, and innovation-related capabilities were not mentioned to be as valuable, based on their nature and the difficulty of measurement, or on them being seen as more emerging capability categories. Conversely, some interviewees, for example, mentioned that communicational aspects are extremely important. Interestingly, the interviewees were not that interested in capabilities related to the suppliers' operations or to the products and technicalities. However, some interviewees seemed to comprise these categories under the other ones, such as delivery or quality.

Some of the information needs align with the utilised capability categories, and the rest can be categorised under these. Regarding the organisational capability category, market trends, supplier competence, and contract information can be seen as related to it. This connection is supported by sub-chapter 4.2.2, which introduces results regarding interviewees' mentions of supplier performance, references, reputation, contracts and financial aspects. Similarly, supplier relationship information can be seen to be included in relational capabilities, since communicational aspects, interactions, and supplier relationships were also discussed in the context. Finally, safety can be categorised under social sustainability, based on the introduction in sub-chapter 4.2.3 of interviewees' mentions in the social sustainability context. Table 17 shows the connections between the two interview themes. Compliance was mentioned in relation to multiple capability categories, such as quality, sustainability, operations, and organisational capabilities, and therefore it is not shown as itself in the categorisation.

Table 17. Connection between the first and second interviews: information needs and capability categories.

Information needs	Capability categories
Quality	Quality
Delivery reliability	Delivery performance
Market trends	Organisation and business
Supplier competence	
Contract information	
Supplier relationship information	Connections
Environmental sustainability	Environmental sustainability
Social sustainability	Social sustainability
Safety	
Supplier innovativeness	Innovation

Regarding challenges in SPM, difficulties related to the technological systems, resources, and data were the most frequent in the interviewed organisations. Regarding qualitative data, especially data availability and reliability, were mentioned by multiple interviewees, and these challenges exist in multiple capability categories. Although the recognised challenges may vary based on, for example, the current role of the interviewee, every capability category had challenges related to qualitative data. Summaries of challenges related to the capability categories, and their management can be found in the following table (table 18).

Table 18. Current challenges in SPM classified by capability categories.

Capability categories	Challenges
Quality	Data is unstructured and comes in large volumes. It is processed manually and therefore a lot of resources are tied. The data analysis process is subjective and inconsistent.
Operations and processes	Unstructured data is analysed manually, and therefore subjectivity exists between suppliers and buyers. Automation or centralised systems do not exist, making quick reactions or prediction difficult.
Delivery performance	Data is unreliable, since changes happen fast and they might not be tracked accordingly. Data is therefore not always accurate, because delivery changes are not recorded and data goes through multiple people and systems.
Organisation and business	Large amounts of unstructured data analysis is based on subjective experiences and manual work. There is a lack of technical solutions, so the information is tied to people and their views, creating issues with visibility and transparency.
Connections	Data might be difficult to collect, or it does not exist. There is a lack of resources, and the data might exist in different forms. Analysis is highly based on subjective experiences and manual work.
Sustainability	Unstructured data is undistributed or comes in large volumes. Because of the large number of suppliers, there are not enough resources for analysis, therefore creating risks regarding visibility. There are not enough resources to validate data. Additionally, every supplier cannot be assessed with the same parameters.
Innovation	Data is undistributed or comes in large volumes. Not enough resources for evaluating and monitoring supplier innovations. Development is hard to track, since data is unstructured and usually communicated in an unstructured and informal manner. Visibility into supplier's developmental projects is poor.

Qualitative data sources were introduced through the same capability categories. Out of the mentioned qualitative data sources, different certificates, legislations, reports, and documents provided by the supplier were mentioned the most. However, informal conversations, formal meetings, and site visits were mentioned multiple times, in every capability category. The interviewees also recognised feedback, technical data sheets, surveys, and questionnaires as qualitative data sources, and mentioned their use in various categories. News reports, media publications, and search engine results were recognised as the more emerging data sources.

The previously recognised information needs can be seen to connect to the qualitative data existing in supply chains, creating cohesion regarding a certain information need and the sources from which it can be collected or generated. Information needs related to operational and technical capabilities are, however combined into one, since the interviewees did not clearly state differences in the information needs regarding that category. Based on a similar principle, the qualitative data regarding organisational and relational capabilities is combined. A categorisation combining the previously introduced information needs with the qualitative data sources discussed in the second interview round can be found in the following table 19.

Table 19. Information needs connected to qualitative data sources classified by capability categories.

<table>
<tr><th>Capability categories</th><th>Information needs</th><th>Qualitative data sources</th></tr>
<tr><td>Quality</td><td rowspan="3">Issues and incidents
Reclamations
Addressing or solving issues
Reliability
Performance
Order information</td><td>Customer complaints and feed-back
Conversations with colleagues
Personnel interviews
Surveys and questionnaires
Standards Certifications
Site visits
Contracts and agreements
Technical data sheets
Quality claims and descriptions of disruptions</td></tr>
<tr><td>Operations and processes</td><td>Meetings
Informal conversations
Internal networks
Reports and analyses
Site visits</td></tr>
<tr><td>Delivery performance</td><td>Meetings
Informal conversations
Internal networks
Certifications
Legislations
Technical data sheets
Supplier’s documents</td></tr>
<tr><td>Organisation and business</td><td>Effect of market conditions on suppliers
Market trends
Size and capacity of the supplier
Certifications and credits and the source of them
Possible sanctions</td><td rowspan="2">Meetings
Informal conversations
Feedback
Internal networks
News reports
Surveys and questionnaires
Media publications
Site visits
Search engine results
Supplier’s documents
Emails</td></tr>
<tr><td>Connections</td><td>Linkage of products
Supplier and employee infor-mation
Cooperation</td></tr>
<tr><td>Sustainability</td><td>Safety across the supply chain
Possible issues
Addressing or solving issues
Materials and recyclability
Emissions and energy use
Programs and agreements</td><td>Certifications
Code of conducts
Legislations
ESG documents
Media publications
Surveys and questionnaires
Meetings
Informal discussions
Site visits
Search engine results</td></tr>
<tr><td>Innovation</td><td>Supplier’s developmental capa-bility
Value possibilities</td><td>Search engine results
News reports
Media publications
Conferences and trade shows
Meetings</td></tr>
</table>

The final part of the interview results focused on NLP potential and possible use cases in the capability categories. Currently, almost all organisations that participated in the interview use NLP solutions in their everyday work. Most organisations mentioned that they have an internal closed system, that utilises NLP techniques, such as LLM, while the rest mentioned that they use an external solution provided by a third-party, for which they have an active business license. The interviewees recognised potential NLP use cases in every category, most of which focused on analysing and creating content and helping the managers, for example, to reduce manual work. NLP has the ability to manage large amounts of unstructured data, and it was mentioned in multiple contexts by the interviewees. A summary of NLP potential related to the capability categories, and their management can be found in table 20.

Table 20. NLP potential in SPM classified by capability categories.

<table>
<tr><th>Capability categories</th><th>NLP potential</th></tr>
<tr><td>Quality</td><td>NLP can search, read and analyse standards and certifications, and use them for comparison. Documents and quality issues can be analysed and linked further to feedback or production issues. NLP can create summaries and reports based on data.</td></tr>
<tr><td>Operations and processes</td><td>Different sources, certificates, legislations and regulatory subjects can be screened, and overviews or summaries can be created. NLP can detect if a supplier has something outdated and suggest possible improvements. Regulatory or sanction lists can be used to check if a supplier follows regulations. Violations can be identified and reports based on them can be generated. Tracking could be automated by analysing emails.</td></tr>
<tr><td>Delivery performance</td><td>NLP can recognise patterns from documents or feedback and connect them to certain parameters. Overall delivery data can be screened, searched and analysed to give indications on development. Supplier can be compared and deliveries, or things that affect them, can be analysed from different sources.</td></tr>
<tr><td>Organisation and business</td><td rowspan="2">NLP can create meeting memos, lists or summaries. Data regarding communication can be analysed and different sources can be compared. Can screen media or news to detect if a supplier has received warnings or been flagged. Issues or risks can be predicted or identified based on different sources. Unclassified data, such as emails or meetings, can be analysed.</td></tr>
<tr><td>Connections</td></tr>
<tr><td>Sustainability</td><td>Large amounts of data can be analysed. NLP can be used to search and summarise reports, certifications or principles, and guide the buying organisation into the right direction. NLP can check what companies are part of a certain program or have certain certificates and compare the findings to supplier documents. Issues or risks can be flagged and solutions suggested.</td></tr>
<tr><td>Innovation</td><td>Large volumes of data can be managed to detect things in order to help with long-time strategies. Algorithms can search innovation related publications regarding new products or technologies, projects and mergers, with certain keywords. Public sources can be analysed to inspect if a supplier has been innovating.</td></tr>
</table>

In conclusion, an important remark is that all the introduced interview results are interconnected. A complete synthesis including all the introduced interview results as one categorisation can be found in appendix D.

5. KEY FINDINGS AND DISCUSSION

This chapter reflects the empirical results to literature analysed in the literature review. Key findings of the research are introduced by providing answers to the research questions determined at the beginning of the research. The goal of the research was to find out how Supplier Performance Management could be improved through the use of proactive measurement and qualitative data (RQ1), which is systematically analysed through the current information needs that exist in Supplier Performance Management (RQ2), supplier performance measures that require proactive measurement (RQ3) and finally, through Natural Language Processing and its potential and possibilities regarding Supplier Performance Management (RQ4). The aim, therefore, is to answer the first research question through the three supporting research questions. The key findings are summarised in table 21.

Table 21. Summary of the key findings.

RQ2: Information needs	RQ3: Proactive performance factors	RQ4: NLP potential in SPM
Supplier information is related to technical and operational, relational and developmental capabilities. Information is needed regarding processes, quality and deliveries, such as quality issues, reclamations and certifications. Information related to relational capabilities is for instance compliance, cooperation, employees and product linkages. In developmental capabilities, information regarding the suppliers' sustainability and innovations is raised, with specific needs being ESG-topics, R&D projects and value possibilities. Qualitative data sources existing in SPM can be connected to the same categories, and they include for example certifications, documents, standards, meeting transcripts and emails.	Proactive measurement is supported by qualitative performance measurements. These measurements can be categorised by supplier's capabilities, which are related to the technical and operational capabilities, such as quality and delivery, relational capabilities such as the organisation itself and its connections, and to developmental capabilities, that consider the supplier's capability regarding sustainability and innovations. These categories can further be divided to key performance aspects, that the buyers appreciate in every category.	NLP technologies, such as data mining and analysis, information extraction, text-pattern recognition and analysis of speaker states can be utilised to create summarisations, patterns, comparisons and different analyses from qualitative data sources. NLP use cases exist regarding every supplier performance category, therefore including quality, operations and processes, delivery performance, organisation and business, connections, sustainability and innovations.
RQ1: Improving SPM through proactive measurement		
Numerous challenges have been recognised in current ways of SPM. The challenges exist in all active phases of SPM; requirement of supplier evaluation, determining the attributes and performance metrics, and the evaluation and monitoring. Challenges can be further introduced through the supplier capability categories and include for example high resource consumption, lack of IS and information sharing, subjectivity of the measurer, data visibility and transparency and data reliability. Proactive measurement and NLP can be used to resolve these issues and improve SPM, by creating NLP use cases through the supplier capability categorisation. The overall use of qualitative data can be used to mitigate the challenges and gain insights regarding the actual performance of the suppliers in a proactive manner.		

The findings presented in table 21 are discussed and analysed further in the following sub-chapters. The sub-chapters contain comparative analysis between the research questions and the findings of the research, building the discussion up towards the main research question. In the Finnish manufacturing industry, the qualitative information needs can be seen to be connected to the proactive measurement metrics that exist for suppliers. Furthermore, the qualitative data needs and challenges existing in SPM can be answered through potential use cases of NLP applications, thus creating overall potential regarding the improvement of SPM through NLP.

5.1 Current information needed in Supplier Performance Management

The first supporting research question (RQ2) of this thesis was: **What are the current information related needs in SPM?** The research question was formed with the goal to research the current information needs that exist regarding suppliers and supplier performance, with a specific focus on the ones that the buyers do not perhaps currently possess as much as they should. This research question was examined through an analysis of existing literature and the of prior interviews conducted in the AI-SIM project.

In the literature (e.g. Akhavan & Zvezdov, 2021; Brinch, 2018; Patrucco et al., 2022; Waller & Fawcett, 2013), information needs are classified through data types, and therefore the categorisation includes data related to products and machines, supply chain events, suppliers themselves, sustainability, and innovations. This categorisation can be seen to connect to the supplier capability bases (Ruuska et al., 2013), which are technological and operational, relational, and developmental capabilities. In the literature, it is emphasised that especially information with a qualitative nature is still lacking (e.g. Boukrouh et al., 2024; Schaltegger et al., 2015; Zheng et al., 2022). The interviews support the phenomenon since the needs requiring more specific and detailed information were raised. As multiple interviewees mentioned, supply chain transparency could be better regarding information in the introduced categories; in like manner, current literature emphasises similar topics (e.g. Enrique et al., 2022; Modi & Mabert, 2007).

Information needs

Procurement professionals emphasised information related to the sustainability aspects of the suppliers, supporting the views of published literature (e.g. Akhavan & Zvezdov, 2021; Brinch, 2018). Additionally, information related to deliveries and the organisation itself was raised as significant. A similar emphasis can be seen in the literature (e.g. Brinch, 2018; Järvi & Munnukka, 2009; Kumar & Pugazhendhi, 2012), as operational and technical aspects are considered important. All in all, the results obtained from both the literature, and interviews are similar in nature. Table 22 categorises the different information needs recognised through the research and answers the second research question of the thesis.

Table 22. Information needs in SPM.

	Information needs: Literature	Information needs: Interviews
Technical & Operational	Production methods [a] Operational performance and governance [a, b] Practices and certifications [a, c] Deliveries [a, b, c, d] Supply chain process [a]	Operational performance Order information Reclamations Issues and incidents Addressing or solving issues Delivery reliability
Relational	Supplier information [b, c] Supply chain structure [c, d, e] Compliance [c, e]	Effect of market conditions on suppliers Market trends Size and capacity of the supplier Certifications and credits and the source of them Possible sanctions Linkage of products Supplier and employee information Cooperation
Developmental	Labour conditions and safety [c, e] Environmental safety [c, e] Legal and civil rights [c, e] CO2 impact and environmental impact [c, e] Product and technology enhancement [f] R&D projects [f, g] Knowledge application [f, g]	Safety across the supply chain Issues related to sustainability Addressing or solving issues Materials and recyclability Emissions and energy use Programs and agreements Supplier's developmental capability Value possibilities
Literature Sources	a: Kumar & Pugazhendhi, (2012) b: Waller & Fawcett, (2013) c: Seok & Nof, (2018) d: Schaltegger et al., (2015)	e: Burgess et al., (2024) f: Jean et al., (2012) g: Patrucco et al., (2022)

Differences, however, exist regarding how specifically the needs are mentioned. As the literature considers information needs from a larger scope, mentioning only the overall themes of information, the interviewees focused more on specific needs that have been derived from the wider themes. Another difference exists regarding information related to supplier innovativeness. Mainly, different aspects of innovation are mentioned, such as knowledge use or product development (e.g. Jean et al., 2012; Patrucco et al., 2022), but specific information needs remain lacking. Although the amount of mentions in the interviews was not that high, specific information needs were still recognised regarding the subject. One explanation for why innovations are not considered much might be that they are still considered one of the more emerging subjects. Another explanation could be that innovation is seen to connect to the other categories, and therefore it is not mentioned on its own.

Qualitative data sources

The needed information can be acquired through various qualitative data sources. The already introduced information needs can be tied to the same capability categories as the qualitative data sources. The procurement professionals highlighted certificates, reports, documents, and conversations as the most important qualitative data sources. Similarly, suppliers' materials and company or industry reports (Deeter-Schmelz & Kennedy, 2004; Handfield et al., 2019; Järvi & Munnukka, 2009) and interpersonal or intraorganisational sources (Järvi & Munnukka, 2009; Kumar & Pugazhendhi, 2012) are emphasised in the literature. Qualitative data sources recognised from the literature and interviews are categorised in the following table 23.

Table 23. Qualitative data sources in SPM.

<table>
<tr><th></th><th colspan="3">Qualitative data</th></tr>
<tr><th></th><th>Literature</th><th>Interviews</th><th>Literature & Interviews</th></tr>
<tr><td>Quality</td><td rowspan="3">Analyses [b]
Company reports [a, b]
Consultants [b]</td><td rowspan="3">Contracts and agreements
Customer complaints and feedback
Certifications
Site visits
Surveys and questionnaires
Standards
Quality claims and descriptions of disruptions
Meetings
Informal conversations
Legislations</td><td rowspan="3">Technical data sheets and databases [b]
Conversations with colleagues [a, c]
Personnel interviews [a, b]
Reports [b]
Supplier's documents [a, b]
Internal networks [b]</td></tr>
<tr><td>Operations and processes</td></tr>
<tr><td>Delivery performance</td></tr>
<tr><td>Organisation and business & Connections</td><td>Outside business associates [b, c]</td><td>Meetings
Feedback
Informal conversations
Site visits
Emails
Surveys and questionnaires</td><td>Internal networks [b]
News reports [b, c, d]
Supplier's documents [a, b]
Search engine results [a]
Media publications [a, b]
Interviews [b]</td></tr>
<tr><td>Sustainability</td><td>Supplier's materials [a, b]</td><td>Certifications
Code of conducts
Legislations
ESG documents
Site visits
Surveys and questionnaires
Meetings
Informal discussions</td><td>Media publications [a, b]
Search engine results [a]</td></tr>
<tr><td>Innovation</td><td>Internal sources [b]</td><td>News reports
Media publications
Conferences and trade shows
Meetings</td><td>Search engine results [a]</td></tr>
<tr><td>Literature sources</td><td colspan="2">a: Deeter-Schmelz & Kennedy, (2004)
b: Järvi & Munnukka, (2009)</td><td>c: Kumar & Pugazhendhi, (2012)
d: Handfield et al. (2019)</td></tr>
</table>

Distinct qualitative data sources are not that much mentioned in the current literature. The subject is analysed through a wider lens, when the interviewees instead focused on more precise data sources. This can be seen, for example, in the quality category, in which literature mainly mentions larger entities, such as company reports (e.g. Deeter-Schmelz & Kennedy, 2004; Järvi & Munnukka, 2009). In contrast interviewees mentioned precise sources, including ISO certificates and quality claims.

5.2 Supplier performance factors requiring proactive measurement

The second supporting research question (RQ3) was: **What kind of supplier performance factors could support proactive measurement?** The aim of this research question was to develop a comprehensive framework or classification consisting of different supplier performance factors, which require qualitative data. The emphasis of this research question lies in the existing literature, since the goal was to utilise the created framework based on the findings to structure the empirical analysis of the thesis. The existing capability categorisations (e.g. Dey et al., 2015; Maestrini et al., 2021; Möller & Törrönen, 2003; Ruuska et al., 2013) tend to partly rely on quantitatively measured performance aspects. This highlights the need for a comprehensive performance framework that solely focuses on the qualitative aspects of supplier performance.

While the current literature emphasises quantitative performance factors, qualitative measures are mentioned in a supporting manner in multiple sources (e.g. Dey et al., 2015; Kazançoglu et al., 2023; Saunila et al., 2021). However, by combining multiple published research, a comprehensive capability framework could be built. The framework consists of three capability bases, which are further divided into capability categories, which are quality, operations and processes, delivery performance, technology/product, organisation and business, connections, innovation and sustainability (Dey et al., 2015; Iddris, 2016; Maestrini et al., 2021; Möller & Törrönen, 2003; Ruuska et al., 2013). The performance categories, on the other hand, consist of certain key performance aspects that work as concrete examples of what the buyers typically look for regarding the supplier’s capabilities. A framework built upon existing literature and consisting of supplier performance aspects, that require analysis of qualitative data, is visualised in table 24.

Table 24. Supplier performance factors requiring proactive measurement.

Capability bases, categories and key performance aspects			
		Literature	Interviews
Technical and operational capabilities [a]	Quality [a, c, d]	Compliance [d], Improvements [b, d, e], Data and reporting [d], Action systems [d]	Certifications Following agreements Consistency Quality systems and reporting Meeting expectations
	Operations and processes [a, b]	Certifications [b], Skills and knowledge [b], Productivity [d], IT infrastructure [b], Visibility and Traceability [b, d, h]	Certifications Industry specific regulations Standards (international or own) Code of conduct Traceability and visibility Flexibility Competence and knowledge
	Delivery performance [a, b, c, d]	Accuracy [b, d, e], Reliability [e], Incoterms [b, d], Regulatory requirements [d], Performance [b, d, e], Protocols [b]	Meeting expectations Time management Accuracy regarding requirements Flexibility Responsiveness
	Technology /product [a, f]	Technology [g], Customisation [g], Durability [g]	Standards Functionalities
Relational capabilities [a]	Organisation and business [a, b, d]	Agility [b], Adaptability [a, b], Financial stability and strength [d], Image [d], Past records [d]	Adaptability Agility Responsiveness Proactivity Financial stability References and past records Reputation, brand strength and image
	Connections [a, b]	IS integration [b], Networking and relationships [e], Reputation [b], Social exchange [b]	Communication and collaboration Relationships Organisation and IT integration and synchronisation Interpersonal trust
Developmental capabilities [a]	Innovation [a, b, c]	R&D achievements [b, e, f], Qualifications [b], Technology use [f, g], Innovation strategy [b, f]	Technology and process development Cooperation and improvement with the buyer Growth goals and targets Achievements
	Sustainability [c, d]	Waste management [d], Clean technologies [d], Eco-friendly materials [d], Pollution prevention [d], Carbon footprint [c, d], Ethical policy [d], Human rights [c, d], DEI [d], Safety [h], Employee welfare [h], Labour practices [h]	Certifications Legislations Standards and guidelines Emissions and pollution prediction Code of conduct Safety Employee welfare Ethical policy Development regarding ESG factors
Literature sources	a: Ruuska et al. (2013) b: Möller & Törrönen, (2003) c: Maestrini et al., (2021) d: Dey et al., (2015)		e: Pressey et al., (2009) f: Iddris, (2016) g: Saunila et al., (2021) h: Kazançoglu et al., (2023)

Based on the interviews, the most important supplier capabilities are technical and operational capabilities. Capabilities related to the supplier's delivery and quality are considered the most important ones. However, all the capabilities existing in the technical and operational capability base are seen to be connected to each other, and therefore, overlapping exists regarding the categories and performance aspects. Similarly, relational capabilities are commonly considered as one entity. Aspects such as references and reputation, brand strength, adaptability, and responsiveness are appreciated. While the emphasis is on qualitative measures, financial figures are still seen to be a significant factor. Additionally, regarding suppliers' relational capabilities and connections, especially communication and collaboration in the buyer-supplier relationship, are extremely important.

The supplier's capability to innovate is valued, but not highly emphasised. Finnish manufacturing organisations see innovations more as an addition than, for example, a requirement, in a way that operational and technical capabilities are considered. However, it is still seen as important that the supplier can bring something to the buyer, and in that way help the buyer themselves develop. That said, the interviewees consider innovating as something that both the supplier and the buyer should do simultaneously. Be that as it may, suppliers with the most developed and advanced technologies or products are perceived as more valuable than others. Additionally, as literature considers environmental and social sustainability as two different themes (e.g. Dey et al., 2015; Maestrini et al., 2021), in Finnish manufacturing organisations they are frequently seen as one entity, which includes important aspects from both themes. Especially safety, environmental subjects and other ESG-factors are seen as high priorities, and if a supplier cannot commit to these, the relationship is ended.

5.3 NLP potential in Supplier Performance Management

The third supporting research question (RQ4) of this thesis was: **How Natural Language Processing could be utilised to support information and improvement needs in Supplier Performance Management?** Although literature researching the use of NLP in the supply chain context exists (e.g. Jha et al., 2022; Treiblmaier & Mair, 2021), current literature does not comprehensively examine the potential of NLP specifically in SPM. The goal regarding this research question was to address the recognised research gap and create a profound framework for utilising NLP in the SPM context, with the aim of connecting recognised qualitative data sources to the potential use cases of NLP. Although technically specific algorithms or techniques were not recognised from the interview material, the mentioned use cases can, however, be connected to those recognised from related fields in existing literature. This enables the development of a comprehensive and concrete framework for NLP use cases and potential techniques identified within them.

The current level of NLP utilisation in Finnish manufacturing organisations varies, but most of the organisations' procurement functions from the research sample utilise LLM models at least on some level. LLM models are used for simple tasks, for instance, information extraction, text summarisation, and as conversational agents. Although the current use cases are not SPM-specific they can be seen as a positive opportunity. However, the current state of NLP in the manufacturing organisations was not seen to have any effect on the interviewees' answers.

The interviewees recognised potential NLP applications through the supplier capability categories. Although potential was discussed regarding every capability category, organisational and relational capabilities were considered mainly as a whole entity. Overall, reading of textual data and documents, comparison and analysis, information searching, and basic task support were emphasised the most. The interviewees mirrored NLP applications multiple times into the lack of resources and therefore suggested use cases related to the assistance of the procurement professionals, regarding routine tasks. However, the efficiency and the precision of NLP algorithms were emphasised, and therefore potential regarding, for example, fact checking and data screening was distinguished.

Current literature does not exactly research the potential of NLP applications in the SPM context. However, use cases in related contexts are recognised and researched more thoroughly. NLP applications have been recognised in the supply chain context and operations management (e.g. Jackson et al., 2024; Korzynski et al., 2025; Tavana et al., 2022), transaction management (e.g. Mariani et al., 2023), and other sub-fields of management (e.g. Chiu & Lin, 2018; Jha et al., 2022; Meyer & Henke, 2023). SPM as it is, has not yet been researched in regard to AI and specifically NLP.

A high-level categorisation divides NLP technologies and algorithms into three groups: text analysis and understanding, text generation and translation, and interactive systems. Frequently researched NLP applications are information extraction, text-pattern recognition and categorisation, text summarisation, data mining and analysis, sentiment analysis, conversational agents, machine reading, and machine translation (e.g. Hirschberg & Manning, 2015; Kang et al., 2024; Khurana et al., 2023; Min et al., 2024). By combining the various NLP applications, existing use cases and the potential use cases identified through the interviews, a comprehensive framework can be created. This categorisation can be seen in the following table 25. The categorisation now combines the recognised use cases with technologies that enable the wanted potential. It is important to note that information extraction and data mining and analysis as technologies are designed to handle large amounts of data (Hirschberg & Manning, 2015; Khurana et al., 2023) and therefore are utilised in every recognised use case. Because of this, these NLP technologies are not included in the following categorisation.

Table 25. NLP technologies and potential in SPM.

Capability category	NLP potential from interviews	NLP technology from literature
Quality	Analysing, reading and searching certifications and standards	Text-pattern recognition and categorisation [b, c] Text summarisation [a, c, d]
	Value comparison between quality documentation, issues, feedback and production issues	
	Summary creation	
Operations and processes	Reading certificates, legislations and sanction lists	Text-pattern recognition and categorisation [b, c] Machine reading [d] Analysis of speaker states [d]
	Detecting issues, violations and outdated attributes	
	Improvement suggestions	
	Analysis of emails	
Delivery performance	Pattern recognition from documents and feedback	Text-pattern recognition and categorisation [b, c] Conversational agents [a, d] Machine reading [d] Analysis of speaker states [d] Text summarisation [a, c, d]
	Improvement suggestions	
	Screening public sources to analyse effects on deliveries	
	Comparing suppliers	
Organisation and business & Connections	Creating meeting memos, lists and summaries	Text-pattern recognition and categorisation [b, c] Machine reading [d] Analysis of speaker states [d] Machine translation [a, c, d] Text summarisation [a, c, d]
	Comparing communicational data	
	Analysis of media and news	
	Comparing suppliers	
	Analysis of emails and meetings	
Sustainability	Analysing large amounts of data	Text summarisation [a, c, d] Text-pattern recognition and categorisation [b, c]
	Summary creation	
	Value comparison between supplier documents and official certificates or programs	
	Detecting issues or risks	
Innovation	Managing large volumes of innovation related publications with certain keywords	Machine reading [d]
	Analysing public sources for innovations	
Literature sources	a: Khurana et al., (2023) b: Kang et al., (2020)	c: Min et al., (2024) d: Hirschberg & Manning, (2015)

Regarding NLP technologies, the most promising ones are data mining and analysis, information extraction, text-pattern recognition, and analysis of speaker states. However, it must be noted that these technologies are examined only as singular applications. In reality, as introduced previously, LLM models combine most of these technologies, and therefore work as a single application.

5.4 Improving Supplier Performance Management through proactive measurement

The main research question of the thesis was: **How management of supplier performance could be improved through proactive measurement?** This research question is supported by the previously analysed questions, making the main question a comprehensive synthesis of all the sub-questions. The goal was to examine current challenges of SPM and connect the findings of the sub-questions with each other to create a comprehensive framework consisting of certain challenges and the improvements of proactive measurement done by NLP.

Current challenges

Based on the existing literature, phases of supplier evaluation are divided in three active phases: requirement of assessment, determination of attributes or metrics of performance, and performance evaluation and monitoring (Monczka, 2009; Thorpe & Holloway, 2008). Challenges existing in the phases are related to either technology or the buying organisation itself. The challenges in the literature are examined on a higher level, and all challenges are not mentioned to exist only in regards of qualitative data, but also in regards of quantitative data. The literature also focuses more on the SPM process as a whole, consisting of, for example, lacking SPM practices (Gunasekaran et al., 2004), lack of visibility and certainty (Burgess et al., 2024; Enrique et al., 2022; Şahin & Topal, 2019), and the nature of the performance metrics and their relation to the buying organisation's goals (Boukrouh et al., 2024; Cousins et al., 2008; Thorpe & Holloway, 2008; Zheng et al., 2022).

However, the interviewees did not recognise challenges based on the phases of the supplier evaluation process, but rather on the introduced supplier capability categories. The goal of the interviews was to get a deeper understanding of the use cases, and therefore the challenges were also discussed at a more focused level, rather than at a general level. Therefore, this difference of views can be explained by the interview structure's way of emphasising the supplier capability categories and recognised use cases. However, as the capability categories can be connected to the third phase of the SPM process, the challenges recognised by the interviewees are also located in this phase.

Therefore, it can be said that the interviewees of the second interview round recognised current challenges that exist in SPM, which can be classified based on the same capability categories that have been previously introduced, as well as by the evaluation and monitoring phase of the supplier evaluation process (Doshi, 2019; Monczka et al., 2009; Thorpe & Holloway, 2008). The recognised challenges currently existing in SPM and supplier evaluation and monitoring can be seen in the following table 26.

Table 26. Current challenges in SPM.

<table>
<tr><th></th><th colspan="3">Current challenges in SPM</th></tr>
<tr><td rowspan="8">Evaluation and monitoring</td><td>Literature</td><td colspan="2">Interviews</td></tr>
<tr><td rowspan="7">High resource consumption [a]
All capabilities do not exist in measurable form [b, a, c]
Unstructured data exists in large amounts [a]
Inefficient information sharing between buyer and the supplier [d]</td><td>Quality</td><td>Subjective and inconsistent process
Large volumes of unstructured data
Manual processing and high resource consumption</td></tr>
<tr><td>Operations and processes</td><td>Lack of centralised IS and automation
Manual processing and high resource consumption
Subjectivity between suppliers and buyers</td></tr>
<tr><td>Delivery performance</td><td>Operations and changes are not tracked accordingly, making data unreliable
Data goes through multiple people and systems unre-corded</td></tr>
<tr><td>Organisation and business</td><td>Lack of IS
Assessment is based on personal views and subjective experiences
Not enough visibility and transparency to supply chains</td></tr>
<tr><td>Connections</td><td>Data is difficult to collect, or it does not exist in con-sistent forms
Lack of resources
Assessment is based on personal views and subjective experiences</td></tr>
<tr><td>Sustainability</td><td>All suppliers cannot be measured on the same attrib-utes
Large volumes of qualitative and unvalidated data
Lack of resources
Risks regarding visibility and transparency</td></tr>
<tr><td>Innovation</td><td>Measures are difficult to develop
Data is undistributed and difficult to acquire
Data is unstructured or informal</td></tr>
<tr><td>Literature sources</td><td colspan="3">a: Sarkar & Mohapatra (2006)
b: Thorpe & Holloway, (2008)
c: Schaltegger et al., (2015)
d: Modi & Mabert (2007)</td></tr>
</table>

The interviewees emphasised challenges related to resources, technological systems, and data. Similarly, high resource consumption and the qualitative nature of data were raised in literature (e.g. Jegadeesh & Wu, 2013; Sarkar & Mohapatra, 2006). However, the current literature emphasises the measurement metrics more than the interviewed procurement professionals, as their current emphasis seemed to be more on the existing data behind the metrics.

Improvement through NLP and proactive measurement

In literature, predictive analytics are seen as a way to analyse the future of operations and, through leading indicators, ad hoc information can be utilised to effectively and proactively manage supplier performance (e.g. Handfield et al., 2019; Hallikas et al., 2019; Jiang et al., 2024). This indicates that through the use of qualitative and unstructured data, organisations gain wider insights into the actual performance and capabilities of their suppliers.

Regarding the challenge of system integration, the data should be generalised and shared through the use of P4.0 technologies, such as cloud computing, IoT, and BDA (e.g. Da Silva et al., 2019; Jahani et al., 2021; Srai & Lorentz, 2019; Zekhnini et al., 2020), as the use of these has been proven to positively affect the organisation's performance and value creation (e.g. Jahani et al., 2021; Srai & Lorentz 2019). As the technologies enable more efficient information sharing and integrated business environments, the existing data can be put into proactive use with the help of NLP. Additionally, to improve data transparency and reduce supply chain uncertainty, qualitative data consisting of leading measurements should be utilised to move towards the use of ad hoc information. Organisation's quantitative objects, on the other hand, must be transformed into more comprehensive ones that include qualitative objects too, to enable a wider range of goals that can further be connected to the suppliers' capabilities.

Overall, SPM practices should be consistent and efficient, as research has shown that performance measurement can positively influence a buyer's competitiveness, organisational learning, and the performance of the suppliers (e.g. Jääskeläinen, 2018; Maestrini et al., 2018). This can be ensured through effective management and use of enabling technologies. From the second phase, determining attributes of performance, all the challenges are related to the buying organisation itself. Similar to the previous phase, these challenges can be reduced or solved through the use of proactive methods. Organisations must transform current management models to include not only quantitative data, but also qualitative and unstructured data.

As stated, proactive measurement goes hand in hand with qualitative measurement. It has been introduced that the information needs, qualitative data sources, and supplier performance categories existing in SPM are all connected. Regarding the same categories, different challenges have been identified, therefore creating clear potential for different use cases of NLP. The said use cases are now created through the capability categories introduced earlier. As the capability categories in the relational capability base are seen to overlap, the use cases are presented as a single entity. NLP use cases regarding the improvement of SPM can be seen in table 27.

Table 27. Use cases to improve SPM through NLP.

	Use case	Challenge	Improvements with NLP
Performance evaluation and monitoring	Quality	Subjective and inconsistent process Large volumes of unstructured data High resource consumption	Access to large amounts of data Automated document searching and understanding Highlighting important attributes, risks and correlations to enable transparency More accessible information to support fast decision-making and quick reactions
	Operations and processes	Lack of automation and IS High resource consumption Subjectivity between suppliers and buyers	Automated document searching and understanding Predictive issue and violation identification Intelligent and tailored recommendations and suggestions Analysis of Emails and unstructured sources
	Delivery performance	Data tracking and unreliability Data validity and inconsistency	Identification of themes, trends, deviations and hidden correlations Intelligent and tailored recommendations and suggestions Mitigation of risks and detection of early warning signs Comparing interesting values to validate information and detect causalities
	Organisation and business	Subjectivity of the measurer Visibility and transparency Lack of IS	Comparing interesting values and proactively detecting causalities Automated analysis of external unstructured data More accessible information to support fast decision-making and quick reactions
	Connections	Data difficult to collect or it does not exist Lack of resources Subjectivity of the measurer	
	Sustainability	Large volumes of unstructured data Data reliability and validity Lack of resources Visibility and transparency	Access to large amounts of data More accessible information to support fast decision-making and quick reactions Highlighting important attributes, risks and correlations to enable transparency Mitigation of risks and detection of early warning signs
	Innovations	Data is undistributed and difficult to acquire Data is unstructured and informal Lack of resources	Access to large amounts of data Automated keyword-based analysis of unstructured or previously inaccessible data

As NLP has been proven to have great potential in SPM, organisations should move towards it by utilising the existing technologies and transforming the traditional SPM into a more digital entity, that instead of focusing on historical data, utilises real-time information and future information. Proactive methods and NLP seem to resolve a large amount of the challenges existing in SPM, all while providing means to address the current information needs regarding suppliers.

6. CONCLUSIONS

This chapter introduces the conclusions of this research. The first sub-chapter 6.1 discusses the achievement of the research objectives. Following that, sub-chapters 6.2 and 6.3 introduce academic and managerial contributions by discussing the implications of this study for current research and managers working in procurement. Sub-chapter 6.4 however, discusses and assesses the quality and existing limits of this research. Finally, future research opportunities are introduced in sub-chapter 6.5.

6.1 Achieving the research objectives

The goal of this thesis was to research the possibilities that proactive measurement can bring to SPM, from the viewpoint of manufacturing organisations. The point of emphasis in this research was on supplier capabilities and the proactive measurement of them. Additionally, the aim was to examine current information needs regarding suppliers and the sources from which this qualitative information could be acquired. Furthermore, current challenges and improvement needs existing in SPM were researched, and these were resolved by examining the potential use cases of NLP.

To achieve the goals determined at the beginning of the thesis, a comprehensive literature review was conducted, and the results were connected to the findings gained from the interview analysis. This thesis combined findings from two interview rounds, the first, consisting of 23 interviews, and the second, consisting of 14 interviews. The goal of the analysis of the first interview round was to determine the existing information needs that buyers have regarding suppliers. These findings were then connected to the findings of the second interview round. The goal regarding the second interview round was to first recognise proactive supplier measurements, and additionally to recognise current challenges existing in SPM and NLP potential regarding them.

The research questions determined at the beginning of the study were all successfully answered. A comprehensive answer was provided regarding every research question, with implications from both the literature study and empirical analysis. Through the answers to the research questions, this study successfully combined supplier information needs, qualitative data sources, performance metrics, SPM challenges, and NLP potential into one, providing profound frameworks regarding supplier performance and improvements through NLP and proactive measurement in SPM.

6.2 Academic contributions

This research adds contributions regarding supplier information needs. With the emphasis being on qualitative and unstructured data, the information needs are not examined from the traditional, quantitative point of view. Although some research regarding qualitative information needs exists (e.g. Patrucco et al., 2022; Seok & Nof 2018), the results of this thesis further broadened the current knowledge. Additionally, through empirical and literature analysis, this research connected the information needs to the capability categories through qualitative data sources, therefore creating a comprehensive framework.

A supplier performance framework consisting of qualitative metrics has not yet received significant attention in operations management research. Previous literature has highlighted quantitative supplier performance metrics, but this thesis introduces a capability framework that focuses on qualitative and proactive metrics. The framework is built upon existing literature (e.g. Dey et al., 2015; Kazançoglu et al., 2023; Maestrini et al., 2021) and considers supplier capabilities in three essential bases, which are further analysed through different performance factors.

Challenges existing in SPM have been researched in previous literature from a general perspective (e.g. Howells, 2024; Boukrouh et al., 2024). This thesis introduces a classification, in which the challenges have been classified by the main phases of the SPM process. Through the empirical analysis, the challenges existing in performance evaluation and monitoring were deepened and divided based on the recognised supplier performance categories. To resolve the SPM challenges, this thesis connects them to potential use cases of NLP, creating a framework that can be utilised even further in existing sub-fields of SPM.

Although research on the use of AI and NLP has been conducted in sub-fields such as marketing and transaction management (e.g. Mariani et al., 2023; Korzynski et al., 2025), SPM has not yet received significant attention. Overall, previous research has focused on AI in the supply chain context on a more general level, and therefore research focusing on more specific use cases is needed. This thesis also adds a new layer of concreteness to the subject, as the use cases in SPM are connected to the actual NLP technologies. Therefore, this thesis contributes to research by examining and combining research subjects that have not previously received significant attention in the context. Valuable insights into the potential use cases of NLP are given by combining the existing information needs, qualitative data sources, challenges, and NLP technologies' possibilities.

6.3 Managerial contributions

This study highlights the different information needs regarding supplier performance, with the focus on information related to proactive and qualitative nature. The categorisation done in this thesis indicates to valuable information types and therefore helps to understand what kind of supplier information should be acquired and utilised, if it has not already been done. As demonstrated in the study, these information needs are closely tied to proactive supplier capabilities, which are necessary to efficiently measure suppliers. Additionally, as it has been proven, effective information sharing between buyers and suppliers can positively affect the performance of both participants. Therefore, the framework of supplier information needs can also be utilised by suppliers, to develop their relationships with the buyers and aim towards more integrated buyer-supplier relationships.

Previously, the focus on supplier performance and SPM has been on quantitative and reactive measurements, while qualitative and proactive measures have not been considered on to a sufficient level. This master's thesis, however, indicates the importance of proactive methods and the importance of utilising qualitative data in the measurement process. The proactive supplier performance factors can be seen to connect to the current supplier information needs, qualitative data sources, challenges, and NLP use cases. The proactive supplier performance factors must be recognised, for the buying organisations to create a profound and comprehensive understanding of all the categories and aspects existing in supplier performance measurement and management. In addition to the capability framework working as a guide for procurement managers, the results can be utilised by suppliers, to recognise their own areas of capability. Through the framework, suppliers can determine their potential core capabilities or identify which capabilities they would need to develop further.

The recognised use cases of NLP, however, can be used as a guide for managers in developing more efficient, transparent, and automated SPM. The NLP framework can additionally help procurement managers to guide resource allocation and possible technology investments related to NLP, since the most potential use cases and technologies are introduced in this study. The organisations that already possess NLP technologies can utilise the framework to even further create value and get access to the capabilities of NLP, while the organisations that do not possess NLP yet can use it as a guide that helps them understand the potential use cases and abilities of current NLP technologies. The overall introduction of existing information needs, data sources containing the information, and technologies used for acquiring the information can be utilised to enable improved information flows and management and therefore make SPM more efficient.

6.4 Research limitations, validity and reliability

To ensure the quality of the research, it is important to assess the limitations associated with the chosen research methodology and context. Saunders et al. (2019) introduce that qualitative data analysis can be validated through consideration of two parameters: research validity and reliability. Research validity refers to the generalisability of the findings and accuracy of their analysis. Reliability, on the other hand, refers to the research replication and consistency. (Saunders et al., 2019) In other words, validity is the ability to explain and analyse the subject of the research objectively, while reliability refers to how the research should be possible to be repeated with similar findings. The validity and reliability of research are primarily based on the researcher's own evaluation and the availability and readiness of the used data (Dubey & Kothari, 2022; Saunders et al., 2019).

As this thesis consists of qualitative data analysis, the parameters cannot be measured in a traditional manner. For example, qualitative data analysis might be difficult to replicate as it is, endangering the reliability as mentioned by (Saunders et al., 2019), but with a clear and in-depth description of the research methodology, similar studies can be conducted. The reliability of the research is therefore ensured through other criteria as well. For example, Saunders et al. (2019) introduce dependability, which refers to the recording of all possible changes that might happen during an interpretive analysis. To achieve high dependability in this thesis, the research methods and process are described in detail in chapter 3, including the methodological choices and data gathering and analysis process.

Reliability might be threatened through researcher or participant error or bias. The participants in the research were selected through purposeful sampling, concentrating on whether the person's profession is related to procurement management and they work in a manufacturing company of a certain size. This decision can be questioned, since other authorities might have added value and more depth to the results. However, the purposeful sampling method enabled great insights into the chosen scope of the thesis, which focused on the procurement functions of large Finnish manufacturing companies.

Moreover, since the research included only organisations from Finland, the repeatability and transferability of the research might be partly neglected. The chosen scope has an impact on the results, and conducting a similar study on organisations from other parts of the world might give differing results. This, however, can be explained by the size of the organisations, their resources regarding AI, and the overall differences in organisational culture.

Validity, on the other hand, might be threatened through participants' views on causal directions and, for example, through personal preferences or recent events that change their perceptions (Saunders et al., 2019). As the interviewees were all professionals working in procurement, the results might be biased since the focus of these interviewees might be mainly on the subjects most familiar or traditional to them. Furthermore, as the first interview round was originally used for other research and the interview structure was not tailored for the purposes of this thesis, the results obtained from it might be limited. Additionally, validity can also be threatened as qualitative data analysis allows possible researcher errors and biases to exist. As all the interviews are verbal reports, which the researchers have personally conducted, the possibility of inaccurate communication and understanding, or memory, is raised. Because of this, it is also possible that another researcher might have gotten slightly different results from the materials.

The threats were minimised by using triangulation methods, such as data triangulation and researcher triangulation. This refers to allowing multiple researchers from different backgrounds to participate in the planning and conducting of the interview study used in this thesis, and utilising data collected from different sources (Hair et al., 2023). By using ATLAS.ti for transcript analysis, coding, and categorisation, larger datasets could be utilised to avoid narrow data collection. In addition, some of the contacted professionals have participated in the previously conducted interviews, and they were contacted based on their previous motivation and high-quality interview participation.

Furthermore, the research sample was quite large, as a combination 37 validated online interviews was utilised. Therefore, a wide range of views on the research subject was ensured, and the possibility of participant bias was mitigated. While it may be believed that online interviews are less efficient than face-to-face interviews, it has been proven that the depth of discussion or themes, and other differences cannot be distinguished between the two (Hair et al., 2023).

6.5 Future research proposals

As this research provided profound and insightful results and combined the subjects of AI and procurement in a way that has not yet gotten attention in research, future research proposals are raised. The proposals are based on the previously introduced research limitations, interesting ideas raised from the literature, and the future potential and utilisation of the results of this thesis. However, it can be noted that overall research regarding the use of NLP in the context of procurement, and especially sub-categories of it, is needed. Doing further research on possible use cases in SCM and SPM would contribute to the understanding of what kind of potential actually exists within AI and NLP.

As the scope of this thesis included only manufacturing organisations from Finland, the next steps could be to widen the scope and, for example, focus on even larger organisations from around the world. The empirical findings from this result could be generalised even further by conducting studies from the views of different geographical locations and, for example, industries and organisation sizes. Including organisations outside the scope of this thesis, the results could be compared, and therefore the framework of proactive supplier measurements and NLP use cases could be both tested and broadened.

Research regarding the actual acquisition of qualitative data is needed. As the data is unstructured, and during the empirical analysis, multiple interviewees mentioned that they have difficulties with data availability (e.g. E1, G1, N1), future research should focus on researching the actual ways to get this qualitative data into use in organisations. This would mean designing new ways to integrate information flows more into organisations, as well as researching possible enabling technologies. Another challenge is that as many of the recognised qualitative data sources are personal sources, such as conversations or emails, in some cases, they are forbidden to document and use in data analysis. Therefore, a way to overcome this barrier should be studied. Since organisations are not allowed to utilise, for example, emails sent by suppliers, perhaps alternative solutions, such as the organisation’s internal communication portals, should be researched.

Additionally, as the subject is technical, research regarding information safety and cybersecurity of the use cases must be studied too. Since the results indicate to the utilisation of data from sources that might be personal, research regarding the safety aspects is needed to actually gain insights regarding the usability of these sources. Overall, as qualitative data and the use of AI are combined, the possible risks or challenges existing in the acquisition of these should be examined even further. This could have valuable implications that can be utilised in organisations planning to implement these technologies in their procurement practices.

Finally, as this study proves the existing potential within the use of NLP and qualitative data, future research should take into consideration the concrete steps required to actually utilise these technologies. Therefore, different roadmaps that guide the managers with the acquisition process of NLP technologies are needed. These roadmaps could further guide the organisations to collaborate in the technological environment and integrate these solutions into use in different functions of the organisations, not only procurement and SPM. Additionally, research regarding the technical aspects of the subject is needed to provide a profound base and guidelines for organisations that are interested in making the shift towards more integrated IS and organisational functions, and the utilisation of AI and NLP.

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APPENDIX A: FIRST INTERVIEW ROUND'S RELEVANT STRUCTURE

Relevant interview theme: Solution users – manufacturing companies

Theme 2. Information Needs Related to Suppliers in Supply Chain Management

- What are the information needs related to procurement or Supply Chain Management that require supplier-related data?
- What type of information about suppliers is needed?
- From what sources (internal and external) and in what ways is this information obtained?
- Do your current solutions provide sufficiently good information related to procurement, suppliers, and supply chains?
- What additional information would be beneficial?
- Can current solutions utilize supplier-related information in decision-making? How could this be improved?
- Do your current procurement, supplier, or Supply Chain Management solutions account for supplier categorization in any way?

APPENDIX B: SECOND INTERVIEW ROUND'S RELEVANT STRUCTURE

Background information:

- Describe your job role? Does it relate to procurement, and how?
- How many years of work experience do you have? What kind of roles have you previously worked in?
- What is your educational background?
- How is your company's procurement function organized?
- Have there been significant changes induced by the adoption of new technologies to support managerial decision-making over the last couple of years?
- Describe your supplier base.

Theme 1: Supplier Capabilities

1. What defines a capable supplier? Could you give example(s) of a capable supplier in a specific situation(s)?

2. What are the capabilities required from the suppliers regarding

technical and operational capabilities?

relational capabilities?

developmental capabilities? (Appendix 1)

3. Which of these capability factors do you value the most and why?

Theme 2: Current solutions for managing supplier performance

4. How do you currently recognize and evaluate the performance (specifically capabilities) of suppliers?

5. How do you currently recognize and evaluate the (social) sustainability performance of suppliers?

6. How do you currently recognize and evaluate the risks related to unethical practices or social responsibility issues of suppliers?

7. Is some kind of system used in the organization to display supplier information, what kind of information does it show and how?

If not, what kind of a system would be helpful for you, for example regarding contents and information visualization?

8. What are the current challenges in measuring supplier capabilities (or performance)?

Theme 3: Data/information

9. Is data on supplier capabilities collected in the following areas?

- technical and operational capabilities?
- relational capabilities?
- developmental capabilities? (Appendix 1)

10. How do you get information regarding supplier capabilities or performance in these capability areas?

11. Are you analysing qualitative data or unstructured data to gather information in these capability areas?

12. Is there anything you wish you had more information about, but currently don't have that information?

Theme 4: Artificial intelligence and Natural Language Processing

13. How could artificial intelligence help obtain information related to the needs you mentioned? Can you give any examples?

14. How could AI or natural/human language processing (NLP) help obtain information related

- supplier compliance?
- supply markets?
- supplier relationships?
- supply chain sustainability?
- supply chain risks? (Appendix 2)

15. How could AI or natural/human language processing (NLP) be used to evaluate suppliers'

- technical and operational capabilities?
- relational capabilities?
- developmental capabilities? (Appendix 1)

Appendix 1: Supplier Capabilities

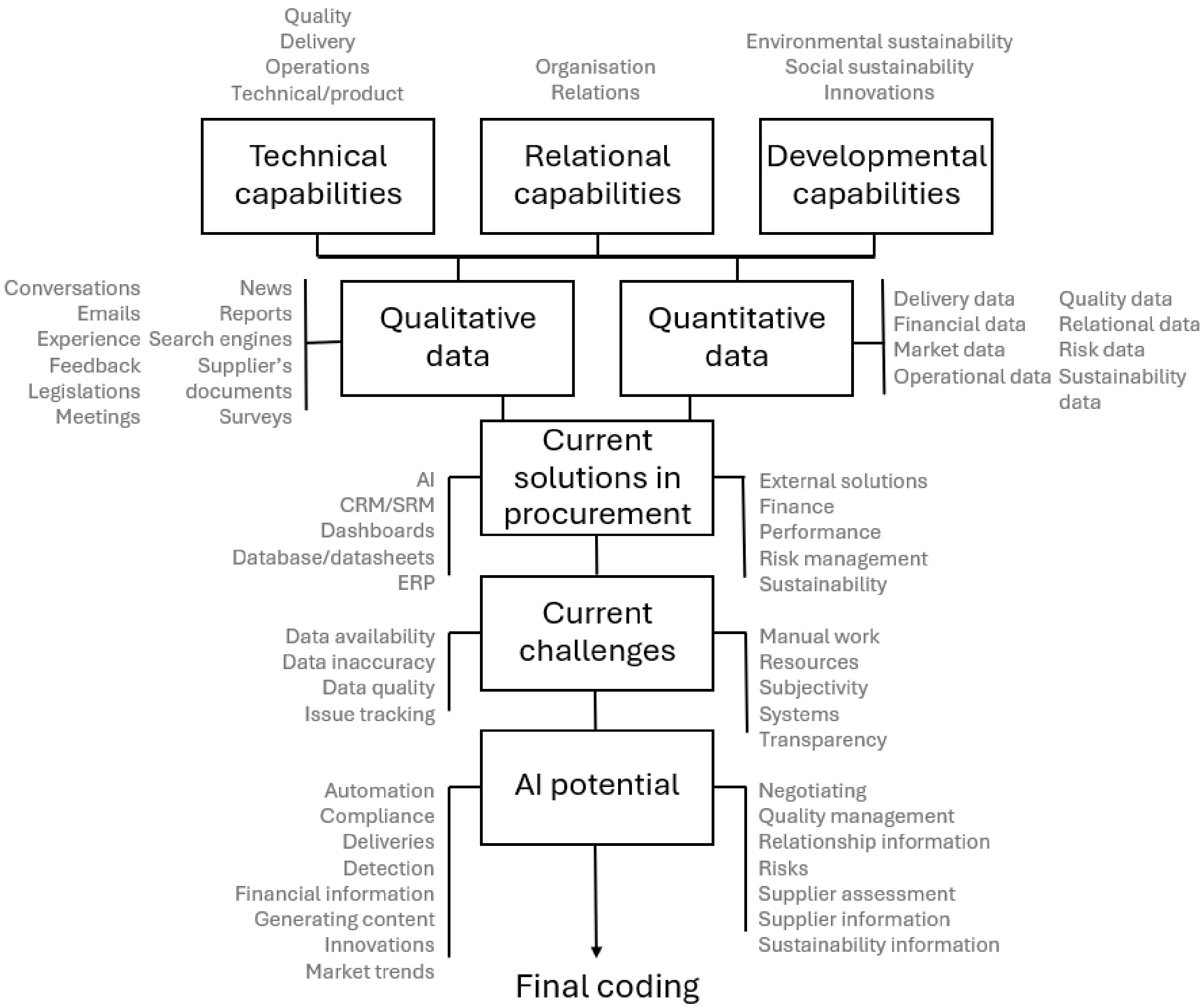
Capability base	Capability categories	Key performance aspects
Technical and operational capabilities	Quality	Requirements and standards, Improvements, Data and reporting, Action systems
	Operational	Certifications, Skills and knowledge, Productivity, IT infrastructure, Visibility and Traceability
	Delivery	Accuracy, Reliability, Incoterms*, Performance, Flexibility, Regulatory requirements, Protocols
	Technical/product	Technology, Customisation, Durability
Relational capabilities	Organisational	Agility, Adaptability, Financial stability and strength, Image, Past records
	Relational	IS integration, Networking and relationships, Reputation, Social exchange
Developmental capabilities	Innovation	R&D achievements, Qualifications, Technology use, Innovation strategy
	Environmental sustainability	Waste management, Clean technologies, Eco-friendly materials, Pollution prevention, Carbon footprint
	Social sustainability	Ethical policy, Human rights, DEI**, Safety, Employee welfare, Labor Practices

*International Commercial Terms **Diversity, Equity and Inclusion

Appendix 2: Information Needs related to Suppliers

Compliance	Supplier relationship information	Sustainability
Supplier risks	Innovativeness	Market trends

APPENDIX C: TREE MODEL OF THE TRANSCRIPT CODING PROCESS



APPENDIX D: FULL CATEGORISATION OF THE INTERVIEW SYNTHESIS

Information needs	Quality Delivery reliability			Market trends Supplier competence Contract information		Environmental sustainability Social sustainability		Safety Supplier innovativeness
Capability categories	Quality	Operations and processes	Delivery performance	Organisation and business	Connections	Environmental sustainability	Social sustainability	Innovation
Challenges	Data is unstructured and comes in large volumes. It is processed manually and therefore a lot of resources are tied. The data analysis process is subjective and inconsistent.	Unstructured data is analysed manually, and therefore subjectivity exists between suppliers and buyers. Automation or centralised systems do not exist, making quick reactions or prediction difficult.	Data is unreliable, since changes happen fast and they might not be tracked accordingly. Data is therefore not always accurate, because delivery changes are not recorded and data goes through multiple people and systems.	Analysis is based on subjective experiences and manual work. There is a lack of technical solutions, so the information is tied to people and their views, creating issues with visibility and transparency.	Data might be difficult to collect, or it does not exist. There is a lack of resources, and the data might exist in different forms. Analysis is highly based on subjective experiences and manual work.	Unstructured data is undistributed or comes in large volumes. Because of the large number of suppliers, there are not enough resources for analysis, therefore creating risks regarding visibility. There are not enough resources to validate data.		Data is undistributed or comes in large volumes. Not enough resources for evaluating and monitoring supplier innovations. Development is hard to track, since data is unstructured and usually communicated in an unstructured and informal manner. Visibility into supplier's developmental projects is poor.
Qualitative data	Customer complaints and feedback, Standards, Informal conversations, Personnel interviews, Surveys and questionnaires, Certifications, Site visits, Contracts and agreements	Meetings, Reports and analyses, Informal conversations, Site visits, Internal networks	Meetings, Legislations, Informal conversations, Technical data sheets, Internal networks, Certifications, Supplier's documents	Meetings, News reports, Informal conversations, Surveys and questionnaires, Feedback, Media publications, Internal networks		Certifications, Code of conducts, Legislations, ESG documents, Media publications, Surveys and questionnaires, Meetings, Informal discussions, Site visits, Search engine results		Search engine results, News reports, Conferences and trade shows, Meetings, Media publications

NLP potential	NLP can search, and analyse standards and certifications, and use them for comparison. Documents and quality issues can be analysed and linked further to feedback or production issues. NLP can create summaries and reports based on data.	Certificates and legislations can be screened, and overviews or summaries can be created. NLP can detect if a supplier has something outdated and suggest possible improvements. Sanction lists can be used to check if a supplier follows regulations. Violations can be identified and reports based on them can be generated. Tracking could be automated by analysing emails.	NLP can recognise patterns from documents or feedback and connect them to certain parameters. Delivery data can be analysed to gain indications on development. Suppliers can be compared and deliveries, or things that affect them, can be analysed.	NLP can create meeting memos, lists or summaries. Data regarding communication can be analysed and different sources can be compared. Can screen media or news to detect if a supplier has received warnings or been flagged. Issues or risks can be predicted or identified based on different sources. Unclassified data, such as emails or meetings, can be analysed.	Large amounts of data can be analysed. NLP can be used to search and summarise reports, certifications or principles, and guide the buying organisation into the right direction. NLP can check what companies are part of a certain program or have certain certificates and compare the findings to supplier documents. Issues or risks can be flagged and solutions suggested.	Large volumes of data can be managed to detect things in order to help with long-time strategies. Algorithms can search for innovation related publications regarding new products or technologies, projects and mergers, with certain keywords. Public sources can be analysed to inspect if a supplier has been innovating.