Value of artificial intelligence in purchasing and supply management

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submitted by

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Summary

Artificial intelligence is a key technology for purchasing and supply management and its usage is still in a nascent stage. For instance, the Volkswagen "Procurement Strategy 2030" stresses its potential to optimize processes and structures - and this applies to the automotive industry and other organizations worldwide. The successful integration of artificial intelligence technologies into operations and supply chains has been limited to a few organizations so far, yet literature and practical applications are gradually emerging. This constitutes a research opportunity on how artificial intelligence increases the value procurement can provide to the organization. Thus, the goal of the doctoral research is to examine and exploit ideas on how artificial intelligence can be utilized in purchasing and supply management. In the past, procurement organizations have often been one of the last functions to be digitized. However, they must keep up with the digital transformation toward industry 4.0, especially with the capabilities of the negotiation partners in business-to-business marketing and sales functions.

This work is composed of five chapters starting with the introduction, followed by three peer-reviewed research papers on artificial intelligence in procurement, and finally the conclusion with a summary, limitations, and future research directions. Thereby, the doctoral research has contributed to the literature on the digital transformation of operations and supply chain management, transaction cost economics, dynamic capabilities, technology adoption, the bundling problem, information processing theory, design science methodology, principal-agent theory, applied ethics for artificial intelligence, and autonomous negotiation agents.

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List of Equations with Connotations

$\forall$=for all

$\sum$ =sum from lower to upper value

σ=standard deviation

μ=mean

List of Abbreviations

ACM=Association of Computing Machinery

ASCM=Association for Supply Chain Management

AI=artificial intelligence

B2B=business-to-business

B2C=business-to-consumer

CCS=Computing Classification System

ChatGPT=Chat Generative Pre-Trained Transformer

COVID=coronavirus disease

E2E=end-to-end

ERP=enterprise resource planning

IEEE=Institute of Electrical and Electronics Engineers

IT=information technology

ML=machine learning

OSCM=operations and supply chain management

PSM=purchasing and supply management

PRISMA=Preferred Reporting Items for Systematic Reviews and Meta-Analyses

SCOR=Supply Chain Operations Reference

Chapter 1 Introduction

"Other organizations such as Google must value flexibility, and therefore have adopted a very different mindset. For our organization, there is a classical efficiency focus with strong project steering and clear business plans (...). Yet, I believe that the mechanism of the past does not necessary work in the future, and we must now set a solid foundation of it!"

Interviewed expert for the literature review in Chapter 2 (Spreitzenbarth, 2022b)

Artificial intelligence is a key technology for purchasing and supply management and its usage is still in a nascent stage (Allal-Chérif et al., 2021; Cui et al., 2022a). The research goal of this dissertation is to examine and exploit ideas on how artificial intelligence technologies can create value for procurement organizations. The work is composed of five chapters starting with the introduction including the motivation, background, and research questions, followed by three peer-reviewed research papers, and finally the conclusions with limitations and future research outlook.

1.1 Motivation

The research approach is to empirically apply different theories and methodological approaches to realize the potential artificial intelligence (AI) in purchasing and supply management (PSM) with concrete examples. Three interrelated studies compose the doctoral research combining quantitative and qualitative research approaches. Procurement can be defined as the process of acquiring goods or services from an external source, aiming to achieve the optimal balance of cost, quality, quantity, timeliness, and location to fulfill specific needs (van Weele, 2018). It is the supply function of the well-known Supply Chain Operations Reference model abbreviated SCOR focused on managing the upstream activities of an organization. Today, it is common for over half of an organization's value creation to originate from its suppliers (Vollmer et al., 2018; Schuh et al., 2022). In an editorial of the Journal of

Purchasing and Supply Management, the digital transformation was highlighted as an opportunity for business-not-as-usual research (Knight et al., 2022). Procurement has recently received increased attention in response to recent supply disruptions such as semiconductor shortages as typical in a supply crisis (Wynstra et al., 2019) but also due to new regulatory requirements such as supply chain transparency, as mandated for instance by the present Supply Chain Act in Germany (The Federal Government, 2022).

Artificial intelligence is a research area that attempts to design mechanisms allowing machines to develop intelligent behavior (Russell and Norvig, 2020) that has been gaining academic and practical attention, whereby there is a need to evaluate, structure, and provide insights on the increasing activities of these emerging technologies often mentioned in conjunction with the catchword Industry 4.0 with significant impact on procurement (Wamba et al., 2021). These developments led to the overarching research question of this dissertation: **What value can artificial intelligence provide for purchasing and supply management?**

The automotive industry is strongly affected by digital technologies (Dremel et al., 2017). Original equipment manufacturers and the entire value chain must undergo a fundamental transformation of their processes and structures to enhance their capacities to make data-driven decisions (Hofmann et al., 2017; Volkswagen AG, 2021; Klee et al., 2023). Across all sectors of the economy, only a few organizations have successfully integrated artificial intelligence technologies into their operations and across their supply chains, but they are starting to emerge (Gunasekaran et al., 2017; Li et al., 2023). Generally, today, buyers typically spend over half of their time on transactional activities (Vollmer et al., 2018; Nitsche et al., 2021a). On the one hand, the increasing significance of information technology (IT) and digital business models lead to a larger share of requisitions requiring procurement to build up new capabilities (Bode et al., 2021). On the other hand, digitalization changes the way procurement organizations work (Handfield et al., 2019).

1.2 Background

Now, what is special about procurement in view of artificial intelligence? Purchasing and supply management is a critical business function with unique challenges and is positioned to tap into the data potential with a myriad of relevant use cases - not only regarding the large share of the overall cost structure that it controls as pointed out in the previous section but also by breaking up data silos and enabling data sharing within the end-to-end (E2E) supply network.

However, the data-driven transformation toward procurement 4.0 is not an end but must provide value to the organization to justify the investment (Ziegler et al., 2019; Chui et al., 2022). The illustration below shows the initial starting point during the exploration phase of the doctorate in the quest to identify relevant applications along with strategic, tactical, and operational procurement processes embodied by the stakeholders, goals, strategy, and recent general research focus.

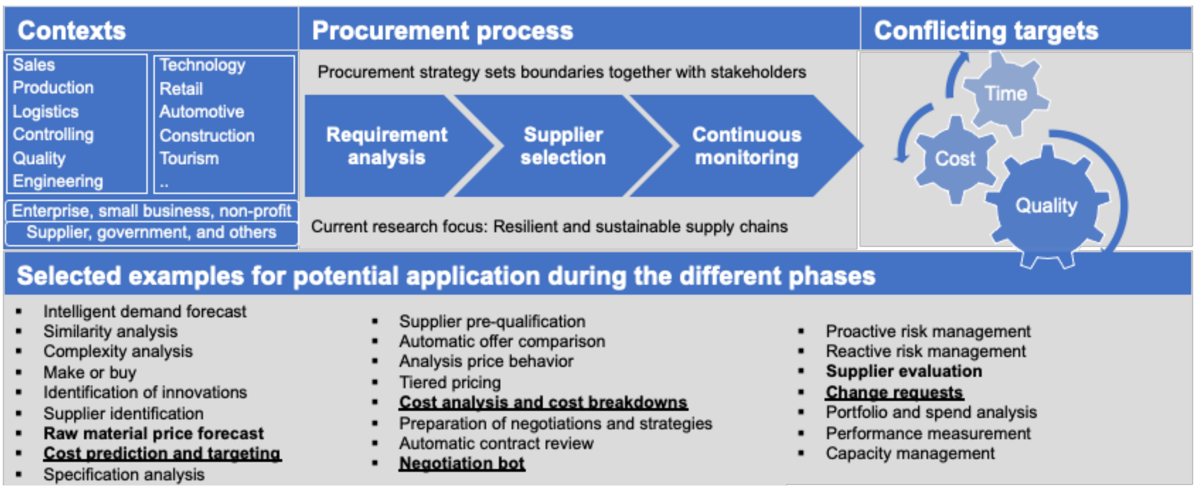

Figure 1: Starting point (own illustration based on Sander, 2017; van Weele, 2018)

Many scholars have studied the digital transformation utilizing different theories and research methodologies upon which this research can be built upon. For example, technology acceptance models propose that several factors influence the decision about how and when users will apply it, notably perceived usefulness and perceived easefulness (Davis, 1989). Dynamic capabilities theory is often employed to understand digital technological adoption

(Spina et al., 2016; Foerstl et al., 2020; Herold et al., 2022) searching for a fit of capabilities with the needs of the organization, especially in environments of rapid change. The competitive advantage of firms is thereby seen as based on distinctive processes, shaped by the assets of the organization, and the development paths it has adopted (Teece et al., 1997).

Today, the perception of procurement is still often associated with a risk-averse cost focused identity (Murfield et al., 2021) that seems to play a role in the technological adoption processes. Yet, the application of artificial intelligence in purchasing and supply management is part of the overall journey of modern procurement organization toward procurement 4.0 (Batran et al., 2017; Bienhaus and Haddud, 2018) for example as outlined in the Procurement Strategy 2030 by the global automotive original equipment manufacturer group Volkswagen (Volkswagen AG, 2021). In the figure below, the keywords and abstracts of the works meeting the inclusion criteria of the review in Chapter 2 were used to generate a word cloud based on natural language processing.

Figure 2: Word cloud in the literature review (own illustration in MonkeyLearn)

In this dissertation, the term artificial intelligence is used as a broad term encompassing machine learning (ML) and is understood as a system's capability to correctly learn from data, using those learnings to achieve specific goals and tasks through flexible adaption (Kaplan and Haenlein, 2019). However, for the literature review in Chapter 2, the definition of the scientific computing society Association of Computing Machinery (ACM) named Computer Classification System (CCS) was utilized that is relevant in information technology research and practice, where AI and ML are both part of computing methodologies as computer-assisted analysis and processing of problems in a particular area (Pagliari et al., 2005). Still, for instance, the second study on the bundling problem utilizes both types of computing methodologies, i.e., for predicting and clustering under this AI umbrella term.

Furthermore, some scholars differentiate between weak AI for assistance or acquisition of specific tasks with individual solutions, general AI where knowledge can be transferred from single solutions to larger topics, and super AI that can meet people spiritually and exceed human capabilities on close to all measures typically accompanied with fears filling science fiction and popular Hollywood movies. Whilst so-called super AI is most likely still in the far future, research institutions around the world work toward reaching general-purpose AI (Russell and Norvig, 2020). For instance, in late 2022, the research laboratory OpenAI trained a new language model called Chat Generative Pre-Trained Transformer (ChatGPT) that is gaining much interest in terms of its performance but also continued criticism of inherent biases (Alba, 2022). As a practical example, a review of the literature on artificial intelligence in purchasing and supply management was created with the generative pre-trained transformer model that can be found in Spreitzenbarth (2022c).

The research studies described in this dissertation focus on what value artificial intelligence technologies can provide to procurement organizations and are largely concerned with weak AI applications that assist professional buyers with data-driven analytical insights forming hybrid human-AI teams that at least currently have been shown to outperform humans or AI alone (Saenz et al., 2020; Cui et al., 2022a; Burger et al., 2023). In this regard, it should be noted that while different artificial intelligence technologies have been utilized in the doctoral research such as supervised learning, natural language processing, and neural networks, these technologies were used to create models, analyze data, explore different approaches to provide new solutions to challenging problems at the intersection between operations and supply chain management (OSCM) with information systems as well as to improve the readability and language of the works. As pointed out for instance in the author guidelines of the Journal of Purchasing and Supply Management, the application of technology should be accompanied by human oversight and control, as authors need to diligently review and edit the generated output of generative AI. While it may produce authoritative-sounding results, there is a possibility of inaccuracies, omissions, or biases that must be carefully addressed (Elsevier, 2023).

Regardless of whether machine learning is part of artificial intelligence or standalone, manifestations of these emerging technologies offer a myriad of relevant research questions and practical applications as part of the information systems of procurement organizations (Handfield et al., 2019) next to already more established technologies such as enterprise resource planning (ERP) or robotic process automation (SAP, 2020; Flechsig et al., 2022). Information technology and information systems play a crucial role in enabling effective supply chain management by facilitating intelligent and coordinated decision-making across the entire network. (Hofmann et al., 2019). Information systems incorporate the technology, people, and processes involved with information in an organization, while information technology is the design and implementation of information within the information system (Peffers et al., 2007).

Artificial intelligence technologies have been shown to be able to support business activities to free time for strategic questions, improve responsiveness, and sustain or gain competitive advantage. In addition, they can support decision-making by analyzing a large amount of data close to real-time and highlighting the most recommendable action possibilities (Raisch and Krakowski, 2021). Worldwide, there are major political initiatives today for instance in the European Union, the United States of America, and China on promoting artificial intelligence with the goal to boost industrial capacities and research activities while promoting safety and fundamental rights as it is considered a key national capability (European Commission, 2022). Yet, many initiatives still fail technically to deliver the expected features or fail to deliver to expected performance outputs (Chui et al., 2022; Mittal et al., 2022).

Artificial intelligence is typically separated from robotics process automation which may be pictured as a software robot that, for example, transfers information from an ERP system to a disjoint contract management system (Schulze-Horn et al., 2020). More generally, big data analytics involves the use of analytics to extract knowledge from large volumes of data, facilitating data-driven decision-making. It is commonly understood as an organizational information technology capability and refers to the ability to leverage analytics in achieving better performance (Gunasekaran et al., 2017). Value in the context of this work is understood as the benefit obtained from the use of artificial intelligence to the organization similar to Brinch (2018). This can include cost savings and cost avoidances, process efficiencies, as well as strategic contributions to risk management and sustainability. Thereby, this dissertation aims to contribute to the current discussion of automation versus augmentation of these technologies for management research in order to develop theory and provide practice with sound advice (Raisch and Krakowski, 2021).

In the global management consultancies McKinsey's (Chui et al., 2022) as well as Deloitte's (Mittal et al., 2022) "The state of artificial intelligence" yearly surveys, the business functions in which organizations adopt AI technologies differ across industries but are over time largely consistent. These are service operations, product development, marketing and sales, especially in the business-to-consumer (B2C) context. Since the negotiation partners in sales and marketing functions seemingly have a faster pace in technology adoption, procurement must speed up in the analytics race. For example, why is the procurement department not utilizing AI to assess supplier risks, while the sales department is using it for demand forecasting? Yet, procurement is in a distinctive position to break up data silos in the supply network in order to profit from marketing insights from the internal organization, such as demand forecasting and purchasing requisition planning but also from marketing insights from the external market with essential industry and product knowledge (Nitsche et al., 2021b; Wamba et al., 2021; Roy, 2022).

Although artificial intelligence research has made significant advancements in a short period, resulting in numerous applications across various domains, organizations are still grappling with the effective implementation of AI technologies (Hofmann et al., 2019). Its vision transcends the limits of human capabilities and is frequently described as a significant element of the fourth industrial revolution (Syam and Sharma, 2018). For instance, the Chief Information Officer of the sports car manufacturer Porsche, Matthias Ulbrich highlighted its cross-functional potential spanning from sales to procurement and production (Ulbrich, 2020). The review of the literature in Chapter 2 underlines that many relevant use cases of AI in PSM lay at the interorganizational or intraorganizational purchasing-marketing interface. The other two studies included in this dissertation are situated at the internal and external purchasing-marketing interface based on dynamic capabilities theory and examine related issues as well as other research such as Nitsche et al. (2021b) or Saenz et al. (2022), especially regarding how the application of artificial intelligence affects buyer-supplier relationships.

Procurement is seen as reverse marketing by many scholars (van Weele, 2018). Sales and marketing as well as procurement are the main boundary-spanning functions of an organization that are connected internally through production or service delivery. Boundary spanners play a crucial role in the digital transformation as change agents, and without them, organizations face difficulties in competing effectively (Saenz et al., 2022). The challenges experienced by both sides are interconnected, specifically through the organizational demand planning process (Seyedan and Mafakheri, 2020). Therefore, in this dissertation, an emphasis is placed on cross-functional use cases, especially at the purchasing-marketing interface.

1.3 Structure

The doctoral research examined key issues of artificial intelligence in purchasing and supply management asking what, why, and how questions combining quantitative and qualitative research approaches. Overall, the studies are situated at the intersection between operations and supply chain management with information systems focusing on what value the application of artificial intelligence technologies can provide to procurement organizations with a focus on the automotive context while generalizing to diverse organizational settings.

In the table below, the theories, research methods, and main contributions of the three studies that compose the dissertation are summarized along with key information about the other research projects conducted during the doctorate that are only briefly summarized and referred to in this thesis. The studies have been assigned to iteratively derived procurement use case clusters and the applied information technologies according to a classification framework of the literature review visualized in Figure 7. For instance, the study of the bundling generator is assigned to the cluster cost analysis and mainly utilized machine learning approaches based on the definition of the Computing Classification System. The selected works that are composing this dissertation are marked in bold script below.

Table 1: Overview of the interrelated studies in the doctoral research

Work	Total cost of ownership prediction with artificial intelligence	Procurement workflow optimization	**Chapter II Review of artificial intelligence and machine learning in procurement**	Artificial intelligence in procurement versus sales and marketing	**Chapter III Designing an AI decision support requisition bundler**	**Chapter IV Ethics for autonomous agents in business negotiations**
Theories	Transaction cost economics	Dynamic capabilities	**Dynamic capabilities**	Dynamic capabilities	**Information processing theory**	**Principal-agent theory**
Research methods	Total cost of ownership case study	Simulation	**Content analysis**	Exploratory research	**Design science case study**	**Design science thought experiment**
Main contribution	Empirical cost prediction for supplier selection	Model to optimize workflows based on a value function	**First academic review of artificial intelligence technology in procurement**	Propositions, why procurement might lag in the adoption	**Novel approach to solving the bundling problem with requisition data**	**Ethical guidelines for artificial negotiators**
Procurement use case	Cost analysis	Strategic supplier management	**Procurement strategy**	Procurement strategy	**Cost analysis**	**Automated negotiation**
Applied technology	Machine learning approaches	Knowledge representation and reasoning	**Theoretical foundations of AI**	Theoretical foundations of AI	**Machine learning approaches**	**Theoretical foundations of AI**
Reference	Spreitzenbarth and Stuckenschmidt (2021)	Spreitzenbarth et al. (2021)	**Spreitzenbarth et al. (2022b)**	Spreitzenbarth et al. (2022a)	**Spreitzenbarth et al. (2023a)**	**Spreitzenbarth et al. (2023b)**

As shown in the table above, during the doctoral research, multiple theories, research methods, technologies, and use cases have been examined and explored. While the studies were iteratively developed during the doctorate building upon each other, from the literature review, over to a case study on bundling requisitions at the purchasing-marketing interface, and finally considering the ethical implications of autonomous negotiation as another relevant use case for buyer-supplier relationships - through the diversify in theory, method, technology, and application individual insights are sought that are synthesized in this thesis combining quantitative and qualitative approaches. Notably the design science methodology is utilized in the research projects described in Chapter 3 and Chapter 4 that is still underrepresented in purchasing and supply management research (Srai and Lorentz, 2019; Stange et al., 2022).

Three studies were chosen for this dissertation out of the six conducted research projects during the doctorate due to their inherent connection as well as their academic and practical contributions. The selected research projects exemplify the diversity in theory, research methodology, procurement use case, and applied technology in order to answer the overarching research question with a focus on the empirical mode of inquiry. Also, throughout the thesis, these research questions are highlighted in bold script. First, the mixed-method review in Chapter 2 offers an in-depth analysis of the state-of-the-art, whereby several use case clusters have been iteratively identified and further assessed through expert interviews. When comparing the prior research activity with the use case attractiveness in terms of business value and ease of implementation in Figure 9, the analysis highlights the need for further research on the cluster cost analysis while for the cluster automated negotiation, the expert assessment was most divergent.

Building upon the review, an automotive case study based on information processing theory was set up related to cost analysis augmenting the skills of expert buyers with artificial intelligence in Chapter 3 to find a novel approach to the bundling problem as a common challenge in procurement organizations. Finally, in the literature review, a gap in ethics for artificial intelligence in procurement was identified. Thus, a design science study was carried out in Chapter 4 of ethics for autonomous negotiation agents as a controversial but also essential use case contributing to a better understanding of AI negotiation that holds the promise of both automation and augmentation.

1.3.1 Review of artificial intelligence and machine learning in procurement

After the initial exploration through the total cost of ownership prediction in Spreitzenbarth and Stuckenschmidt (2021) and the workflow simulation optimization in Spreitzenbarth et al. (2021), it was evident that a structured review of the existing body of knowledge was needed. Thus, a systematic review of the literature was conducted to answer the following three research questions: **What are the common use case clusters and characteristics of the literature on artificial intelligence and machine learning in purchasing and supply management?** In addition, **how is the current state of artificial intelligence and machine learning in purchasing and supply management assessed from a practical perspective?** And finally, **what are the gaps in the literature and potential directions for future research and applications of artificial intelligence and machine learning in procurement?**

The review was essential for the doctorate to gain an overview of the field. Thereby, the mixed-method review based on dynamic capabilities theory follows the content analysis methodology of Mayring (2014) where the material evaluation is extended by expert interviews to triangulate the results. The work offers a comprehensive summary of the state-of-the-art in research and practice and was utilized to prioritize use cases for the following steps in the research endeavor.

1.3.2 Designing an AI decision support requisition bundler

Secondly, building upon the findings of the literature review, a research project was set up with a case study organization on solving the well-known bundling problem in procurement through a novel approach based on artificial intelligence technologies in particular natural language processing and supervised learning. The objective was to create a design artifact that is practically useful in order to deduct design principles to identify further cost savings potentials by bundling requisitions across the organization. This led to the research question: **How to**

design an information system that supports buyers to identify further saving potentials by bundling requisitions?

A prototype of a bundling generator was set up with a focal organization in the automotive industry utilizing the design science methodology based on Peffers et al. (2007) building on information processing theory. The collection of the requirements of the case study organization as well as the evaluation of the design artifact is particularly relevant for technology solution providers and contributes to the literature on spend analysis and strategic procurement planning as not only information on past purchases was utilized for the analysis of bundling opportunities but also more uncertain and imprecise purchasing requisition data.

1.3.3 Ethics for autonomous agents in business negotiations

Finally, in the third study of the dissertation, based on the finding of the review of the literature where no study was identified that focuses on the ethical implications of the application of artificial intelligence in purchasing and supply management, the effects of autonomous agents in business negotiations was selected since the expert assessment of this cluster in the expert interviews of the literature review differed widely. In addition, the ethical lens has largely been underrepresented in purchasing and supply management leading to the research question: **What are the major ethical implications of autonomous negotiation agents at the buyer-supplier interface and how could they be addressed?**

Also following the design science methodology, design principles for the development and operation of autonomous negotiation agents have been derived. In addition to the discussion of the related literature, a thought experiment has been set up, which questions five different normative ethics traditions namely pragmatic, utilitarian, virtue, role, and deontological might consider, what they may see as the main ethical implications, and how to address them when autonomous agents interact with other autonomous agents, humans, or hybrid human-AI teams.

Chapter 2 Review of artificial intelligence and machine learning in procurement

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Artificial intelligence and machine learning are key technologies for purchasing organizations worldwide and their usage is still in a nascent stage. This systematic review offers an overview of the state-of-the-art of literature and practice, where 46 works meeting the inclusion criteria were interactively classified in 11 use case clusters. The work follows the content analysis approach where the material evaluation was empirically enriched with 20 interviews to assess the cluster's business value and ease of implementation through triangulation through this mixed-method approach.

Furthermore, the Computer Classification System as the de-facto standard in information technology was utilized for clarity in the terminology of these emerging technologies. In matching the literature with the interview results, a mismatch was found between the reviewed literature and the expert's assessments. In particular, the cluster cost analysis deserves higher research attention as well as supplier sustainability. In addition, there seems to be a gap in the literature on artificial intelligence and machine learning in the operational area of procurement, which many believe to be first considered due to data availability. The insights from literature and interviews may guide procurement executives to better understand the dynamic capabilities needed to successfully steer the organization in the transformation toward procurement 4.0.

2.1 Introduction

Purchasing organizations, suppliers and partners produce massive quantities of data providing substantial potential for added value (Brinch, 2018), but this potential is often not yet fully exploited (Handfield et al., 2019; Allal-Chérif et al., 2021). While artificial intelligence is a research area that attempts to design mechanisms allowing machines to develop intelligent behavior, machine learning is typically understood as the study of computer algorithms that improve through experience using data (Russell and Norvig, 2020).

There is a need to evaluate, structure, and provide insights on the increasing research and practical activities of emerging technologies often mentioned in conjunction with the catchphrases Industry 4.0 and digital transformation with significant impact on procurement (Knight et al., 2022). The study reports on their potential applications, i.e., what are the emerging themes and current gaps for future research, and thereby contributes to answering the overall research question of this dissertation. This is significant because only a few purchasing organizations have successfully integrated these evolving technologies into their operations and across their supply chains. Practitioners and academics seek to understand which technologies perform what types of tasks and best address specific needs to increase the value proposition of procurement (Seyedghorban et al., 2020). This led to the first research question:

- **What are the common clusters and characteristics of the literature on artificial intelligence and machine learning in purchasing and supply management?**

The procurement function has already seen advances in technological innovation, such as the introduction of electronic procurement and enterprise resource planning systems. However, the potential of the fourth industrial revolution may generate a new wave of digitalization (Batran et al., 2017; Bienhaus and Haddud, 2018). Following Monczka et al. (2020), purchasing and supply management, also called procurement is recognized as the strategic approach to efficiently managing the upstream value chain, encompassing the planning and acquisition of an organization's present and future requirements. Thus, this work focuses on the supply function of the Supply Chain Operations Reference model developed by the professional society Association for Supply Chain Management (ASCM).

There are distinct literature reviews of AI and ML in the neighboring domains of production, i.e., Li et al. (2017) and logistics, i.e., Woschank et al. (2020); however, for the field of PSM, there is not yet an exhaustive and systematic review published in a peer-reviewed journal, yet already several literature reviews have been conducted as conferences papers and student theses. The closest work that has been published after conducting this literature review is by Guida et al. (2023) in the Journal of Purchasing and Supply Management, which has mapped the offerings of information technology providers to an established purchasing process model by Spina (2008) and conducted a focus group with purchasing managers. Now, what is special about procurement in view of artificial intelligence and machine learning? Purchasing and supply management is a critical business function with unique challenges and is positioned to tap into the data potential with a myriad of relevant use cases - not only regarding the large share of the overall cost structure that it controls but also by enabling data sharing within the supply chain network (Nitsche et al., 2021b; Wamba et al., 2021; Roy, 2022).

Literature seems to be divided on the question, of whether machine learning is an integral part of or standing as a separate field next to artificial intelligence. This study follows the understanding of the leading subject textbook by Russell and Norvig (2020) making a distinction between AI and ML in order to provide a more precise terminology and to distinguish more clearly between the different applied technologies. Thereby, this review utilizes the ontology of the Computing Classification System of the Association for Computing Machinery as the de-facto standard in computer science whereby AI and ML are both part of computing methodologies as computer-assisted analysis and processing of problems in a particular area (Pagliari et al., 2005).

This is the first known review at the cross-section of information systems with operations and supply chain management to apply this framework and utilize the related "ACM Guide to Computing Literature" to strengthen the comprehension and assessment for the coding, what types of technologies have been applied. In addition, it was soon apparent to the researchers, that a practical perspective on the state-of-the-art described in the literature is essential for providing a comprehensive report. Thus, expert interviews were conducted to triangular the results. To enrich the review with relevant practical insights from the interviews, power quotes are inserted throughout the study and this dissertation as below. The list of expert interviews can be found in the Appendix in Table 12 following chronological order.

When asked about their understanding of these technologies, expert V from Germany said: *"Many talk about imitation of human minds, but human mind is very complex. I associate AI with solving complex problems and automation that try to solve problems like a human using a machine."* Expert XV from China said: *"Let a machine think and act like humans. The technology has the potential to reduce costs, improve quality, and automate decisions."*

The history of artificial intelligence can be dated back to a workshop at Dartmouth College in 1956 in the United States of America. Since then, there have been several waves of AI with high hopes but also disillusion of expectations, the so-called AI winters in the 1970s and 1990s (Russell and Norvig, 2020). The general understanding of artificial intelligence has shifted considerably over time, whereby scholars mostly have a common understanding of what constitutes artificial but differ in what is understood as intelligence. Thus, it is a widely used term yet characterized by preconceived notions and interpretations that relate to the idiosyncrasy of different fields (Cui et al., 2022b).

The term machine learning was popularized by IBM researcher Arthur Samuel in 1959 working on a program that could play the board game checkers (Russell and Norvig, 2020). As Sundar Pichai, Chief Executive Officer of the information technology cooperation Google pointed out: “*Machine learning is a core, transformative way by which we’re rethinking how we’re doing everything and we’re in early days, but you will see us - in a systematic way - apply machine learning in all these areas”* (Ziegler et al., 2019, p. 11). Artificial intelligence and machine learning technologies can support business activities to free time for strategic questions, improve responsiveness, and sustain or gain competitive advantage. In addition, they can support decision-making by analyzing a large amount of data close to real-time and highlighting the most recommendable action opportunities (Raisch and Krakowski, 2021).

Artificial intelligence and machine learning techniques are typically separated from robotics process automation which may be pictured as a software robot that, for example, transfers information from an ERP system to a disjoint contract management system (Schulze-Horn et al., 2020). More generally, big data analytics involves the use of analytics to extract knowledge from large volumes of data, facilitating data-driven decision-making (Schoenherr and Speier-Pero, 2015; Nguyen et al., 2018). It is commonly understood as an organizational information technology capability and refers to the ability to leverage analytics in achieving better performance (Gunasekaran et al., 2017).

While other works are structured around various different terms of applied algorithms and explore their applications as well as strengths and weaknesses, the main objective of this inductive review is to empirically explore literature and practice with a focus on relevant use cases that will not only have an impact on procurement operations, but also on the entire organization, external partners, and society. Thereby, this empirical mixed-method research aims to contribute to the current discussion of automation versus augmentation of these technologies for management research to develop theory and provide practice with sound advice (Raisch and Krakowski, 2021). This led to the second and third research questions:

- **How is the current state of artificial intelligence and machine learning in purchasing and supply management assessed from a practical perspective?**

- **What are the gaps in the literature and potential directions for future research and applications of artificial intelligence and machine learning in procurement?**

The remainder of this chapter is organized as follows: The next section describes the methodological approach, then the content analysis is outlined from the material collection, descriptive analysis, to category selection with boundary conditions and common themes to answer the first research question. This is followed by cluster evaluation through expert interviews and material evaluation to answer the second research question. Finally, the results are discussed to answer the third research question, and the conclusions are summarized with contributions to theory and practice as well as limitations and opportunities for future research.

2.2 Material and methods

The methodology applied is the content analysis based on Mayring (2014), where the material evaluation is extended by expert interviews as suggested as suitable by Seuring and Gold (2012). The exploration of literature and practice is summarized in the figure below according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses statement abbreviated PRISMA, as utilized for instance by Bäckstrand et al. (2019).

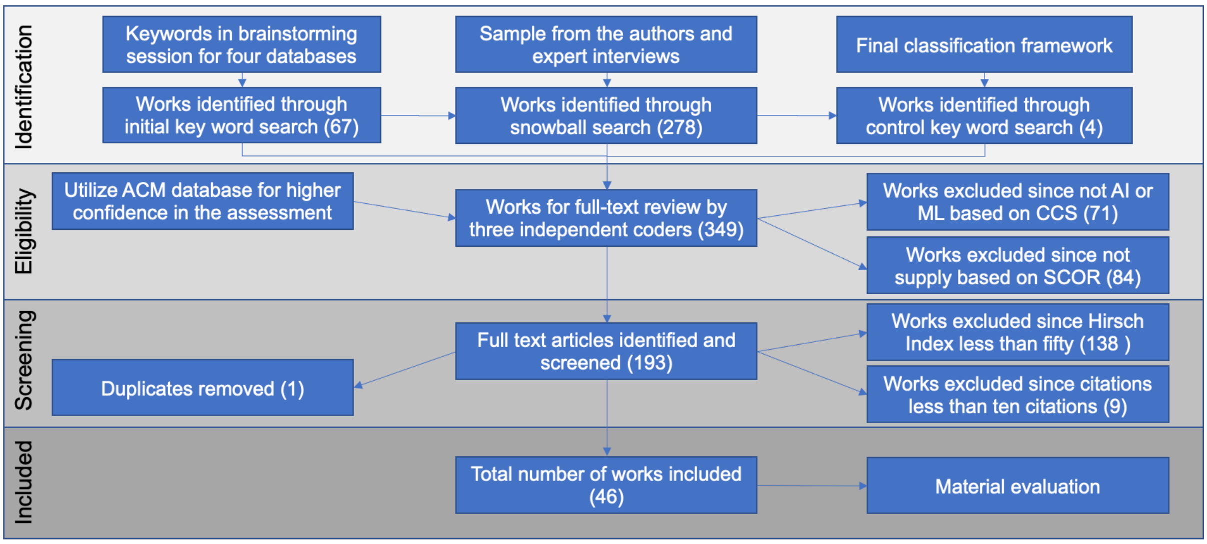

Figure 3: Overview of review process (own illustration based on Page et al., 2021)

The digital transformation is not an end but must provide value to the organization to justify the investment (Ziegler et al., 2019; Chui et al., 2022). Dynamic capabilities theory is often applied to better understand digital technological adoption (Spina et al., 2016; Foerstl et al., 2020; Herold et al., 2022) while finding a strong fit between capabilities with the needs of the organization, especially in organizational environments of rapid change. The competitive advantage of firms is seen as based on distinctive processes, shaped by the assets of the organization, and the development paths it has adopted (Teece et al., 1997).

The state-of-the-art of artificial intelligence in purchasing and supply management is arguably in a nascent phase (Bienhaus and Haddud, 2018; Schulze-Horn et al., 2020; Seyedghorban et al., 2020; Allal-Chérif et al., 2021; Nitsche et al, 2021a; Cui et al., 2022a; Guida et al., 2023), for this phase inductive theory building is proposed as appropriate in Durach et al. (2021), which offers an approach for stepwise theory building that avoids the so-called miner approach, which consists of mere descriptions or enumerations. Robotic process automation in procurement, for example, is already further advanced in the adoption in many organizations as showcased, for instance by Flechsig et al. (2022).

Methodologically Durach et al. (2021) built on their earlier work "A New Paradigm for Systematic Literature reviews in Supply Chain Management" arguing that literature reviews in operations and supply chain management have not yet reached their full potential, because the systematic analysis of the literature has mostly looked backward and focused on identifying gaps, developing research agenda, and categorizing the literature - and thereby failed to challenge or advance theoretical perspectives. Therefore, they differentiated between four different types of literature reviews namely inductive theory building, contextual explanations, theory testing, and interpretive sense making - researchers should thereby strive for consistency between the current state of knowledge on a certain topic and the type of literature review.

Nascent applies to situations with highly limited understanding and agreement on the relevant phenomena and the connections between them. In addition, definitions are typically either non-existent or inconsistent. This was evident since the initial keyword search of this review, whereby common definitions and terminology were found missing in the literature on artificial intelligence and machine learning in procurement. An inductive review is iterative, moving between empirical findings, coding, and generalized propositions as an objective search for small-scale generalization. It may lead to the exploration and identification of patterns asking what, why, and how questions with a conceptualization of theoretical constructs often with an invitation for further work on the phenomenon opened by the review. Inductive reviews entail the careful examination and critique of the extant literature in order to identify themes, relationships, and gaps in understanding (Durach et al., 2017).

After the initial keyword search, it was evident that a common wording basis for AI and ML in PSM was lacking. Therefore, an established framework from the field of computer science was utilized as a clearly defined ontology with precise terminologies. Three independent coders classified the literature according to the CCS and the SCOR models that were utilized as a demarcation guideline to focus on the supply function that was detailed by the concept of the strategic, tactical, and operational levels of procurement (Spina, 2008; van Weele, 2018; Vollmer et al., 2018; SAP, 2020) with an open investigation in search of main themes following Mayring (2014) and Thomé et al. (2016). This aligns with the initial exploration of the doctoral dissertation outlined in Figure 1 based on the encompassing literature of big data analytics in operations and supply chain management.

The work was carried out with the goal to extend theory following an inductive approach by making it "*more dense by filling in what has been left out - that is by extending and refining its existing categories and relationships*" (Pratt et al., 2006, p. 238). Due to the current nascent maturity stage, it was decided to exploratory go through the literature loosely tied with the Extended Purchasing Process as an established reference model described in van Weele (2018) which is illustrated in Figure 4 below in order to find common denominations and headlines for grouping the chosen studies into research lines (Mayring, 2014; Thomé et al., 2016). Thereby, the coders each added open codes as needed and discussed with one another to obtain a consistent meaning across each researcher analyzing the data like Murfield et al. (2021). After discussing initial open codes, the researchers used axial coding across the themes that emerged throughout the analysis (McCracken, 1988).

One model that is commonly utilized to depict the major procurement processes across different organizational settings is the Extended Purchasing Process as a wheel of iterative processes with supplier relationship and performance management in its midst. It describes source on top of the wheel that encompasses strategic and tactical activities, from spend and demand analysis until contracting - as well as operational purchase-to-pay activities, which start with the search and financial requisition approval for specific purchasing items and conclude with the payment to the selected suppliers. This abstraction of in practice diverse procurement tasks and procedures is not unique in combining strategic, tactical, and operational activities but other comparable reference models are less detailed in terms of the specific activities. Thus, the Extended Purchasing Process has been selected for this study. In the figure below, the identified use case clusters along the strategic level of procurement are mapped to the established process model in light grey coloring, the tactical level in orange coloring, and the operational level in light yellow coloring.

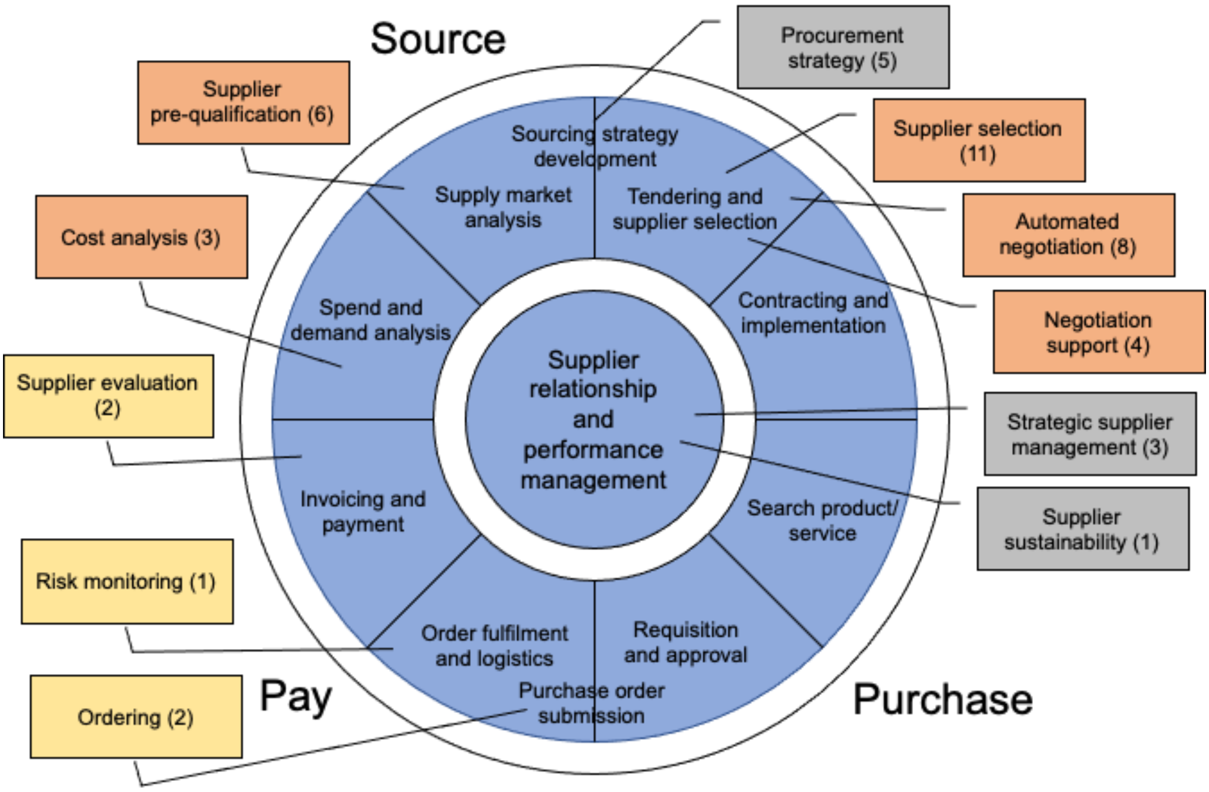

Figure 4: Use case clustering mapping (own illustration based on van Weele, 2018)

Next to the Extended Purchasing Process illustrated above, another often utilized procurement reference model is by Spina (2008) along the strategic, tactical, and operational levels of procurement. These three dimensions are also utilized in practical reports by supply chain consultancies and information technology providers (Vollmer et al., 2018; SAP, 2020). In the dissertation summary, the iteratively derived use case clusters of this review are similarly mapped to Spina's reference model in Figure 19 in order to analyze the resulting clusters drawing on different standard frameworks.

Furthermore, inclusion criteria were iteratively devised as the literature was more fully understood. Still, even if the criteria are adequately designed, researchers may apply the criteria subjectively. Yet, the theoretically deduced scheme with predefined categories and precise definitions enhances the reliability of the coding and - together with detailed discussions within the research team - the internal validity of the findings (Durach et al., 2017). In addition, de-contextualization and abstraction of the content analysis outcomes allow for claiming a certain degree of generalization for the findings and hence external validity. The classification was discussed between the coders with an inter-rater agreement rate for measuring ex-post agreement between decoupled coders Cohen's kappa of 0.88. Since a perfect agreement between coders can hardly be reached because interpretative elements bear a subjective element, it is still expected to be at least eighty percent (Mayring, 2014). When disagreements between coders occurred, they resorted to the article and included the third coder to resolve it.

In this process, 71 of the 349 identified works were excluded since they did not focus on AI and ML computing methodologies according to the CCS, 84 were excluded since they did not explicitly address supply issues according to the SCOR model, and in one instance when two articles by the same authors were seemingly similar, the later article was excluded. Thereof, there were 55 publications with a "Hirsch index" of at least 50 according to the "Scimago Journal and Country Rank" as of January 4th, 2022 applied similarly to the research of Wynstra et al. (2019). The index expresses the number of articles h in the publication outlet that has received at least h citation, thereby quantifying both research productivity and scientific impact (Wynstra et al., 2019). This threshold was defined after conducting a sensitivity analysis. In addition, the Scimago database was found most comprehensive and was therefore chosen despite criticism of between-category comparability that is better accounted for in indexes such as "Source Normalized Impact per Paper" (Spina et al., 2016). Due to this criterion, the majority of included works are from journals with a few major conferences such as the International Joint Conference on Artificial Intelligence and cross-disciplinary scientific workshops organized by the Institute of Electrical and Electronics Engineers (IEEE).

Finally, 46 works remained having at least 10 citations according to Google Scholar correspondingly as of January 4th, 2022 applied similarly to the literature review Ni et al. (2020). Again, since Google Scholar was the most comprehensive source, it was utilized for the citation count despite its shortcoming in terms of adjusting the results based on previous searches. The citation bar was set comparatively low since much research is conducted recently but was still applied to ensure a baseline of academic reception of the work. Insights of recent papers that might be missed out due to the time lag of citations are at least referenced in the section material evaluation, i.e., Allal-Chérif et al. (2021) and Cui et al. (2022a). Also, more than twenty percent of the screened works are popular contributions highlighting the practical interest. This grey literature such as white papers is not included in the sample due to the inclusion criteria, however, when appropriate their insights are referenced in the material evaluation e.g., from technology providers such as Vollmer et al. (2018), Booth and Sharma (2019), and Papa et al. (2019). The exploration of the existing body of literature has been contemplated with interviews to assess the clusters similar to the literature review by Woschank et al. (2020).

Based upon the research questions and the first exploration of the literature, an interview guideline was developed to conduct semi-structured interviews that generally work well in high-uncertainty situations with open-end questions (McCracken, 1988; Mayring, 2014). In total, twenty-nine persons were invited, whereof twenty interviews were conducted between October 19th, 2020 and March 24th, 2021. The experts were purposely selected to choose information-rich cases concentrating on procurement executives, AI and ML technical experts as well as procurement analytics specialists expected to have both the domain expertise and the technological toolbox to assess the clusters.

The sample includes a variety of different professional backgrounds in terms of industry, geographical region, organizational size, and level of hierarchy as summarized in Table 12. In addition, further factors were taken into consideration such as age and gender to capture a holistic picture with diverse points of view. Sampling bias and selection bias was remedied by involving multiple researchers and considering different perspectives (Seuring and Gold, 2012). In addition, non-responsive bias was addressed by follow-ups and iteratively, purposefully selecting further experts until saturation in the interview assessment was reached.

A definition of each of the clusters was provided in the interview invitation that was created by the coders in a brainstorming session along the sub-dimensions of business value and ease of implementation adapting an approach of a consultancy report on the topic by Ziegler et al. (2019) for their quantitative assessment. The coding and analysis were conducted by the same three researchers as of the literature analysis using a selective protocol as the interviews had an open, narrative character and the researchers were interested in specific topics of the interview guideline depending on the experience of the interviewee (McCracken, 1988; Mayring, 2014). Afterward, the interview notes were sent to the interviewees for review and potential elaboration in case of misunderstandings, whereupon one expert added specific details. Others provided additional references to literature and practical applications that arose during the interviews.

Lastly, it is important to note that the review started with the data search, whereby the coding scheme and the interview guideline were developed and continuously improved in parallel when the first data exploration and the interviews took place simultaneously in an iterative process as summarized in the PRISMA statement in Figure 3. Following open science principles, the data from the analysis of the literature and the interviews can be found under creative commons license as data references for future research at Spreitzenbarth (2022a) and Spreitzenbarth (2022b). Thereby, no specialist software was used other than Microsoft Office tools and in-depth discussions among the coders.

2.3 Content analysis

As highly cited reviews within the field such as Brinch (2018), Nguyen et al. (2018), and Woschank et al. (2020), this inductive work follows the content analysis approach with material collection entailing a process of search and delimitation of articles, descriptive analysis providing characteristics of the studied literature, and category selection aiming to construct a classification framework (Seuring and Gold, 2012; Mayring, 2014).

2.3.1 Material collection

To answer the first research question on common themes and distinctive characteristics, the relevant literature is examined in this section as well as the following descriptive analysis and category selection. The initial keyword set had been set up by examining other reviews such as Gunasekaran et al. (2017), Li et al. (2017), and Woschank et al. (2020), prominent publications in the field, and the judgment of the authors in a brainstorming session. Using more than one database to identify relevant literature contributes to preventing any research from being missed and reducing any possible publication bias (Thomé et al., 2016; Durach et al., 2017). The search has been conducted with four commonly used databases similar to Brereton et al. (2007) and Nguyen et al. (2018), namely Emerald, IEEE Xplore, Google Scholar, and Science Direct between September 2nd and October 17th, 2020.

According to Spina et al. (2016), the authors must scan and filter all articles of a wider set of publications before selecting and coding papers. However, when conducting the first examinations of the literature, not sufficient material with a distinct focus on AI and ML in PSM could be identified. Thus, the keywords were first varied in different ways and tried several databases, and no constraints were applied to publication time or mediums. The resulting search strings have been constructed using Boolean operators adapted to the syntax for each search base: (Artificial intelligence OR AI OR machine learning OR expert systems OR chat bot) AND (procurement OR purchasing OR sourcing OR savings OR supply management OR supplier OR category management OR buyer OR negotiation).

Overall, the search results were similar across the databases with only a few relevant works that could be identified. This is likely because research seems to be in an early phase of maturity since there is evidently no common wording basis and publications can be found more often in general technology-focused journals than in specific supply-focused journals. Still, through Science Direct, Google Scholar, and Emerald several key publications could be identified and with IEEE Xplore it was possible to find specific niche works. In total, 71 articles were identified that served as the basis for forward and back searches to ensure a full and exhaustive review (Thomé et al., 2016; Durach et al., 2021) in addition to the sample of the authors and the interviewed experts until the end of 2021 leading to 349 articles based on the title, keywords, and abstract as illustrated in the PRISMA statement in Figure 3. The completeness of the systematic search was reviewed on January 4th, 2022 by a control search based upon the classification framework described in the section category selection, where only four further works were identified. Although literature reviews are likely never complete, this provides some evidence that it has reached a certain degree of comprehensiveness.

2.3.2 Descriptive analysis

At the intersection of different domains, it can be challenging to determine, whether a paper should be reviewed in detail by using only titles, abstracts, and keywords (Brereton et al., 2007). Therefore, the identified publications were analyzed and discussed by three coders based on the iteratively refined coding scheme summarized in the table below. This descriptive analysis provides the reader with essential information about the literature sample. Categorical information is shown with the count of all 349 identified works and the final 46 works based on the inclusion criteria described in the PRISMA statement along with the free-text categories listed at the bottom of the table.

Table 2: Overview coding scheme for the review of the literature

Category **(if applicable following)**	**Class with the count in declining order** **(meeting criteria/ identified)**
Search base	Snowball (44/278), IEEE Xplore (1/31), Google Scholar (1/24), Science Direct (0/10), Emerald (0/6)
Publication class	Academic (46/263), popular (0/86)
Publication type	Journal (43/166), Conference (3/76), white paper (0/47), blog (0/30), thesis

	(0/12), book (0/9), press release (0/5), video (0/4)
Publication domain (adapted from Spina et al., 2016)	Information systems (21/97), operations and supply chain management (16/87), management (6/129), purchasing and supply management (3/25), marketing (0/6), law (0/5)
Author gender	Male (40/262), female (6/65), no classification (0/22)
Industry (United Nations, 2008)	No specific reference to industry (21/218), manufacturing (10/67), transportation and storage (6/22), construction (4/11), retail (4/10), public (1/12), others (6/0), agriculture (0/6)
Data source (adapted from Seyedan and Mafakheri, 2020)	Historical data company (39/231), simulation data (3/5), data based on other studies (2/75), historical data public (1/16), expert judgments (1/13), historical data laboratory (0/9)
Data type (Ni et al., 2020)	Supplier data (37/235), manufacturing data (5/17), demand data (3/31), sensor data (1/2), customer data (0/43), product data (0/11), sales data (0/6), inventory data (0/4)
Organizational type (adapted from Spina et al., 2016)	Large enterprise (24/167), non-specific (18/158), public (4/20), small and medium-sized enterprises (0/3), NxO (0/1)
Study context (Spina et al., 2016)	Exploratory (36/307), theory building (10/42), theory testing (0/0)
Research method (adapted from Spina et al., 2016	Model building (25/102), case study (15/151), simulation (3/5), conceptual (2/26), literature review (0/52), Delphi (1/3), survey (0/5), interviews (0/3), design science (0/1), experiment (0/1), replication study (0/0)
Theories (adapted from Spina et al., 2016, refined with Tate et al., 2022)	No theory mentioned (33/307), fuzzy inference theory (6/11), transaction cost economics (3/10), game theory (3/3), Dempster-Shafer theory (1/1), Resource-based view (0/4), information processing theory (0/3), rough set theory (0/3), dynamic capabilities (0/2), social network theory (0/2), utility theory (0/1), agency theory (0/1), paradox theory (0/1)
Analytics Maturity Framework level (Gartner, 2018)	Level 4 predictive analytics (26/162), level 3 prescriptive analytics (14/48), level 2 diagnostic analytics (4/72), level 1 descriptive analytics (2/67)
Technology category	ML (25/110), AI (21/167), general (0/71)
Comments by reviewing ACM database	No similar works found (23/269), similar to AI/ ML (10/34), classified as AI/ ML (8/22), overruled (5/11), classified as general (0/9), in the database without classification (0/3), similar to general (0/1)
CCS function (ACM, 2012)	Machine learning approaches (19/56), knowledge representation and reasoning (15/59), distributed artificial intelligence (5/25), learning paradigms (3/27), machine learning algorithms (2/23), control methods

	(1/6), learning settings (1/4), no classification since general or duplicate (0/72), theoretical foundations of artificial intelligence (0/57), search methodologies (0/9), planning and scheduling (0/7), natural language processing (0/3), computer vision (0/1), cross-validation (0/0)
SCOR function (ASCM, 2017)	Source (46/236), enable (0/75), plan (0/16), make (0/13), deliver (0/6), return (0/3)
Procurement type	Tactical (32/104), strategic (9/102), operational (5/30), no classification since not focused on procurement or duplicate (0/113)
Use case cluster	Supplier selection (11/46), automated negotiation (8/17), supplier pre-qualification (6/10), procurement strategy (5/72), negotiation support (4/18), strategic supplier management (3/28), cost analysis (3/12), ordering (2/14), supplier evaluation (2/8), no classification since not focused on procurement or duplicate (0/113)
Criteria fulfilled?	No (0/303), yes (48/48)
Publication name, Hirsch index (Scimago), year, citations (Google Scholar), corresponding author, author affiliation, affiliation country, publication name, keywords, abstract, comments of discussions among the coders	

As summarized in the table above, most works meeting the inclusion criteria of this review do not explicitly mention applied theories, but some works are theoretically based on fuzzy logic, transaction cost economics, and game theory. In addition, some works distinctly focus on concrete applications in particular of manufacturing, transportation, and construction but most works are rather abstract and not directed toward the particulars of specific use cases or industries. The organizational setting for most of the identified research is on larger organizations in general, while some focus specifically on public procurement. Yet, no major work was conducted in small and medium-sized enterprises or non-profit and non-government organizations denoted with NxO in the table above.

The main data sources are historical data from companies, simulation data, secondary data, and expert judgments. Many authors come from the United States of America, the Netherlands, Australia, Iran, and the Greater China region based on the author's organization, e.g., the National Taiwan University of Science and Technology with three publications. There are only a few authors with two works meeting the inclusion criteria: K. L. Choy, W.B. Lee, and V. Lo from the Hong Kong Polytechnic University, and C. Wu from Xiamen University working with D. Barnes from the University of Westminster. The most cited work Kuo et al. (2010) combining sustainability and supplier selection based on a machine learning technique.

During the systematic analysis of the literature, the cross-authorship was analyzed. However, due to the diversity of authors and institutions in almost twenty countries, no further insights were gained - just like by the cross-analysis of keywords and abstracts. Therefore, no bibliometric citation analysis or funding analysis was conducted. The most common keywords are supplier selection, supply chain management, neural network, case-based reasoning, artificial intelligence, machine learning, artificial neural network, Bayesian Network, and data envelopment analysis. The keywords and abstracts of the works meeting the inclusion criteria are visualized as a word cloud through natural language processing in Figure 2 in the introduction of the dissertation.

The main research methods are case studies, followed by model building, and simulation. However, no replication study was identified in the review indicating a gap in theory-building work in this evolving field. In addition, no study was identified focusing on ethical questions or their impact on organizational performance. The number of publications of each outlet is illustrated with the colorings of the bars representing the methods in the figure below. Overall, there is a wide spread of 30 different mediums mostly from technical-oriented journals and the wider OSCM field, i.e., Expert Systems with Applications, International Journal of Production Economics, and the Journal of Supply Chain Management. Surprisingly, no work meeting the inclusion criteria was published when the literature review was conducted in the Journal of Purchasing and Supply Management or Supply Chain Management: An International Journal.

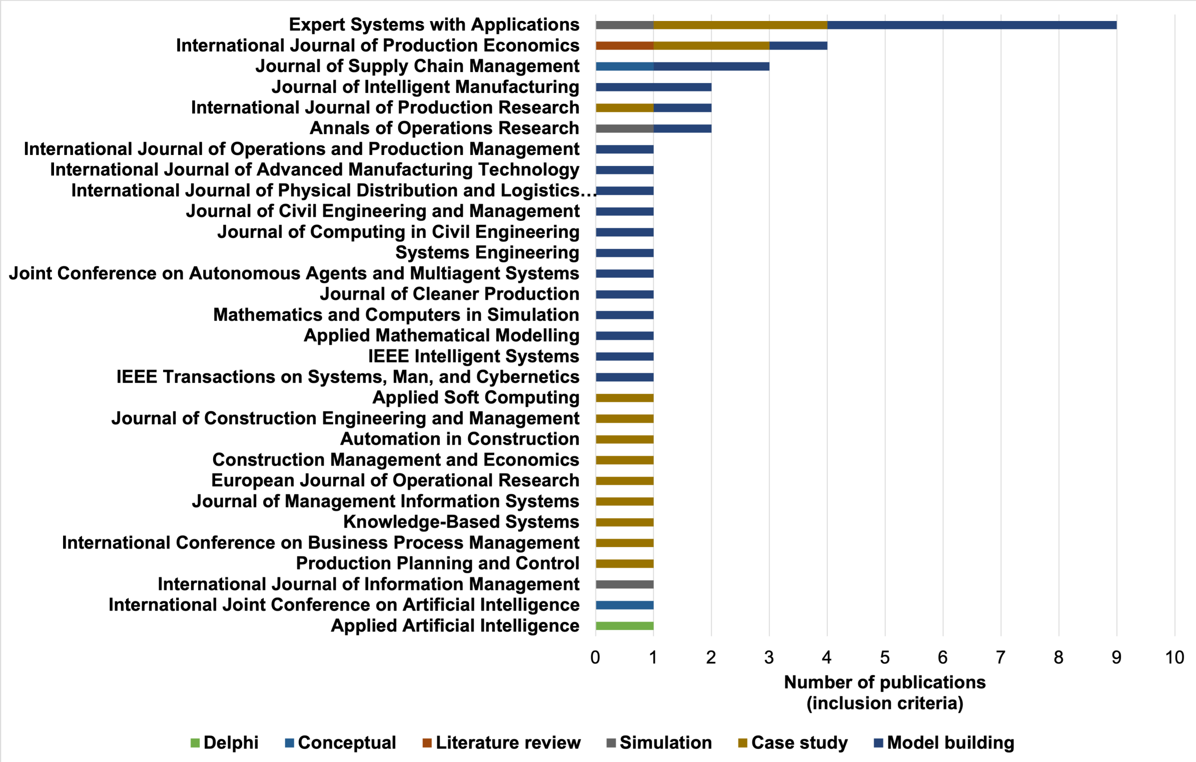

Figure 5: Overview of publication mediums of the ranked works

The publications meeting the inclusion criteria are spanning 32 years from 1989 until 2020 as summarized in Figure 6 below. The literature elaboration was not restricted to commencing at a certain point in time but before the 1989 article by Matwin et al. about an expert system for negotiation support, not much research that pertains sufficiently on AI and ML in PSM could be identified during the systematic search. Some may argue that an over thirty years old paper on this topic might be outdated. However, during the literature analysis, it was evident that the earlier works provided valuable insights that are still relevant to readers today. Most articles can be attributed to machine learning with about sixty percent of publications and citations according to the CCS while works not focused on AI or ML were categorized as general, e.g., robotic process automation.

Time analysis has been performed on the procurement use case clusters as well as the sub-dimensions of AI and ML with different temporal buckets. However, there were no major findings other than the overall rising trend with both more diversity in applications and applied algorithms. Thus, the works were segmented into five-year periods also known as lustrums as by Wynstra et al. (2019) illustrated in the figure below. The bars represent the publication number of the strategic, tactical, and operational levels of procurement and the grey line of AI, and the yellow line of ML technologies. As of submitting this thesis, the last lustrum is likely to continue the constantly rising trend of the increasing number of publications of the last years.

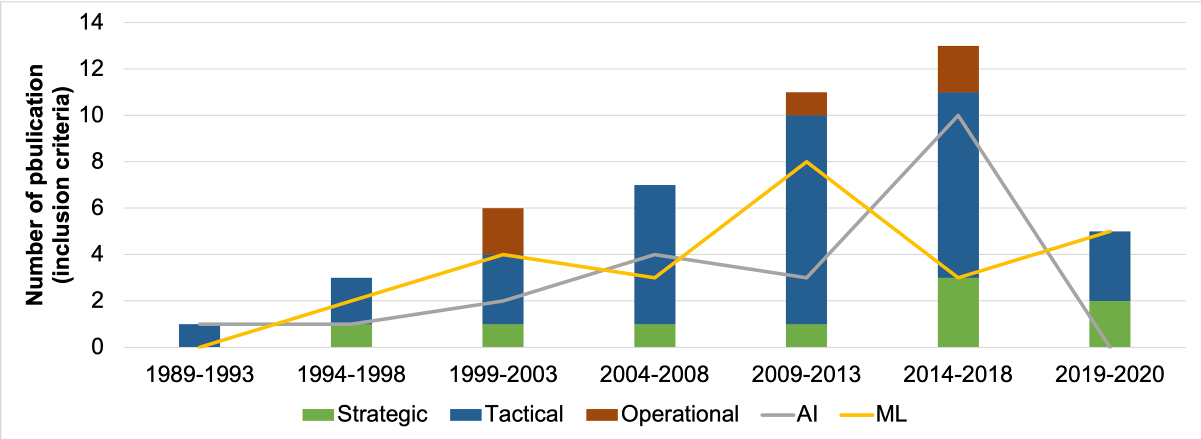

Figure 6: Number of publications over years in temporal buckets

As illustrated above, there seems to be a gap in the operational area, which many believe to be first considered due to data availability, analytical maturity, and data quality (Vollmer et al., 2018; Ziegler et al., 2019; Chui et al., 2022; Mittal et al., 2022) that will be further analyzed in the subsequent sections.

2.3.3 Category selection

Structural dimensions and analytical categories constitute the classification framework. Categories are derived from the material under investigation, employing an iterative process of category building, testing, and restating by contrasting and comparing the categories and the underlying data (Mayring, 2014).

Firstly, according to the CCS as an up to six-tiered hierarchical ontology, AI and ML are both sub-categories of computing methodologies as computer-assisted analysis and processing of problems in a particular area (Pagliari et al., 2005). Ontologies are modular representations of knowledge and are well-established in many areas of computer science (Stuckenschmidt and Klein, 2003). The CCS has been applied to match reviewers, as a classifier for digital libraries, e.g., of the ACM and CiteSeerX, and in some literature reviews in computer science, for instance, Frolov et al. (2020). There are thirteen level 1 and eight level 2 classifications for computing methodologies. The level 2 class artificial intelligence includes the following eight level 3 classes with their respective level 4 classes:

- Natural language processing with speech recognition, machine translation, and information extraction among others
- Knowledge representation and reasoning with vagueness and fuzzy logic, probabilistic reasoning, and semantic networks among others
- Planning and scheduling with planning under uncertainty and multi-agent planning among others
- Search methodologies with game tree search, randomized research, and heuristic function construction among others
- Control methods with motion path planning and computational control theory among others
- Theoretical foundations of AI (abbreviated for philosophical/theoretical foundations of artificial intelligence) with cognitive science and theory of mind
- Distributed artificial intelligence with multi-agent systems, intelligent agents, and mobile agents among others
- Computer vision with computer vision problems

The level 2 class machine learning includes the following five level 3 classes with their respective level 4 classes:

- Learning paradigms with supervised learning, unsupervised learning, and reinforcement learning among others

- Learning settings with batch learning and learning from implicit feedback among others
- Machine learning approaches with classification and regression trees, neural networks, and Markov decision processes among others
- Machine learning algorithms with ensemble methods, regularization, and feature selection among others
- Cross-validation

Out of the 46 included works in this literature review, eight publications were directly classified with high confidence based upon the ACM Guide to Computing Literature with three million mainly technical entries, where most listings are already CCS categorized. For another ten publications, the review of the ACM Digital Library provided additional confidence to the coders. In cases when a work has several, in terms of the inclusion criteria conflicting categorizations, the coders referred to the category weighting as well as to the full text to confirm their assessment as shown in the PRISMA statement in Figure 3. In five instances, the classification of the work in the ACM database was not followed after intensive discussions between the coders. During the coding, especially the CCS level 4 classes were found useful by the coders. Yet, if detailed definitions were added to the instructions on how to classify with the CCS, it could be even more helpful for scholars in other fields as information technology is becoming ubiquitous. For instance, in search of a precise definition of computing methodologies, it was necessary to refer to the United States National Library of Medicine as the CCS guideline does not provide it yet. Moreover, some categories are based on wording typically used in AI and ML literature, for example, decision support systems with expert systems fall under the top-level information systems.

Secondly, the SCOR model describes the key operations and supply chain management activities associated with all phases of satisfying customer demand. Of the six primary supply chain management processes, the supply function is seen as processes that procure goods and services to meet demand (ASCM, 2017). Also, SCOR has been utilized as a process-oriented framework for academic supply chain management analysis in several works such as Brinch (2018) and literature reviews such as Ntabe et al. (2015) or Chehbi-Gamoura et al. (2019). This general understanding of PSM is further detailed using the strategic, tactical, and operational levels and the established Extended Purchasing Process as the starting point for the search for common themes as described in the methodological section. Thereby, eleven clusters were iteratively created, discarded, and rephrased by reading through the literature and discussions among the coders to find common denominators (Mayring, 2014; Thomé et al., 2016) along these dimensions:

- Strategic level with procurement strategy, strategic supplier management, and supplier sustainability
- Tactical level with supplier pre-qualification, cost analysis, negotiation support, automated negotiation, and supplier selection
- Operational level with risk monitoring, ordering, and supplier evaluation

When combining the CCS with the iteratively derived clusters, trends are visible in terms of which technologies have been used for which application. This is illustrated in the figure below with the use case clusters on the x-axis with the number of publications in different colorings and the level 3 categories of AI below and ML above to the y-axis.

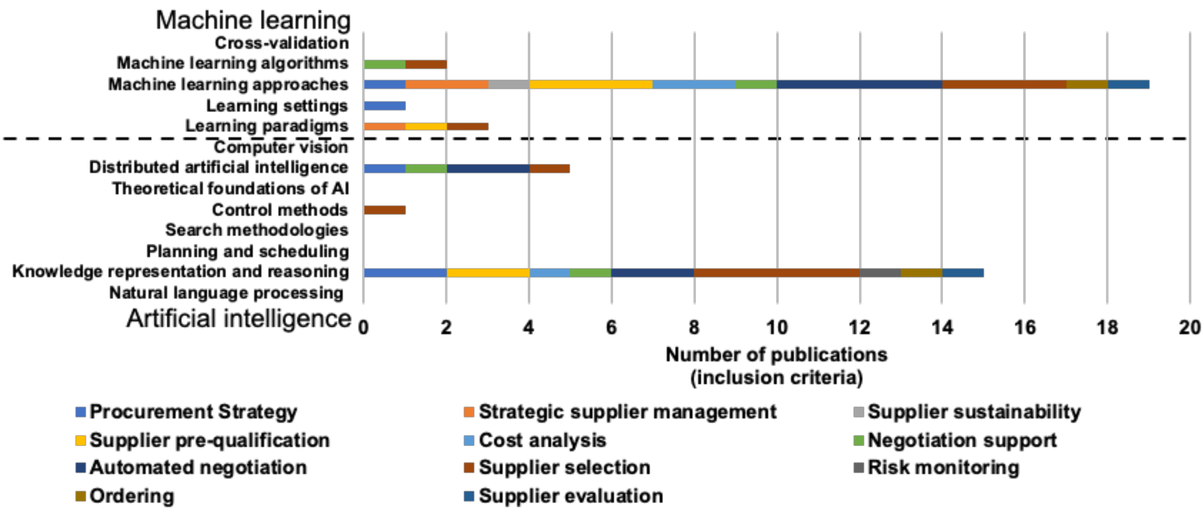

Figure 7: Classification framework of the literature review

As visualized below, some CCS classes have seldom been applied so far in purchasing and supply management such as cross-validation, computer vision, or planning and scheduling. In addition, from the perspective of the applied algorithms, there is a variety of different use cases. Machine learning approaches such as neural networks are widely researched especially for automated negotiation. Finally, knowledge representation and reasoning is extensively utilized especially for dealing with uncertainty in supplier selection, and distributed artificial intelligence is often utilized for examining the actions of multiple agents.

2.3.4 Expert interviews

To answer the second research question about the assessment of the common themes from a practical perspective, expert interviews have been conducted to enrich, compare, and contrast the findings from the analysis of the literature. The experts have been selected based on the criteria outlined in the methodological section. All interviews were conducted online taking between 45 and 60 minutes by at least two researchers. The interviews took place amid the coronavirus disease (COVID) pandemic disrupting supply chains worldwide but also fostering digitalization initiatives. Surprisingly, none of the interviewees referred to the coronavirus disease as a driver for AI and ML initiatives. Yet, events like these might have skewed the expert assessment more toward supply chain resilience and transparency factors. One often highlighted aspect in the interviews was the need to connect prototypical concepts early to existing systems, otherwise, the costs of introduction with training are often too high in addition to the necessary maintenance for operative deployment. Another reoccurring theme was the necessity to build up trust in the decision-making.

Most technology acceptance models propose that several factors influence the decision about how and when users will apply it, notably perceived usefulness and perceived easefulness (Davis, 1989). This has been taken as the basis to develop a scoring system for business value composed of financial value, customer value, and strategic value as well as ease of implementation composed of input data, know-how, and change effort has been set up to evaluate the clusters in analogy to similar analysis from consultancies (Ziegler et al., 2019). The quantitative assessments of the clusters are summarized in the table below along with their standard deviations σ and average values μ.

Table 3: Overview of the use case cluster assessment in the expert interviews

Cluster	σ	**Business Value**				**Ease of implementation**			
		Financial	Customer	Strategic	μ	Input data	Know-how	Change effort	μ
Procurement strategy	1.2	3.5	3.2	4.1	**3.6**	2.5	2.4	2.5	**2.4**
Strategic supplier management	1.0	3.8	3.2	3.6	**3.5**	2.8	2.8	2.8	**2.8**
Supplier sustainability	1.0	2.7	3.5	3.9	**3.3**	2.5	2.6	2.8	**2.6**
Supplier pre-qualification	1.1	3.1	2.8	3.0	**2.9**	3.0	3.0	3.1	**3.0**

Cost analysis	1.1	4.3	3.4	3.6	**3.7**	3.6	3.5	3.3	**3.4**
Negotiation support	11	3.5	2.7	2.9	**3.0**	3.2	3.4	2.8	**3.1**
Automated negotiation	1.1	3.6	2.8	2.6	**3.0**	3.3	2.8	2.9	**3.0**
Supplier selection	1.0	4.0	3.0	3.7	**3.6**	3.0	2.9	2.7	**2.8**
Risk monitoring	1.2	3.9	3.8	3.6	**3.7**	3.3	3.1	3.7	**3.3**
Ordering	1.2	2.9	3.0	3.0	**3.0**	4.0	3.6	3.5	**3.7**
Supplier evaluation	1.1	3.2	3.0	3.7	**3.3**	3.4	3.5	3.7	**3.5**
σ	**1.1**	**3.5**	**3.1**	**3.4**	**3.3**	**3.3**	**3.0**	**3.1**	**3.1**

Generally, the technological adoption of digital technologies can be approached from the consideration of the feasibility or technical difficulty, and the use case or value to the business (Ziegler et al., 2019) as shown in the evaluation of the expert interviews in the table above. Overall, the experts showed a preference for the business value over the ease of implementation. The interview guideline and anonymized list of interviewees in chronological order when they have been conducted are provided in the Appendices.

2.3.5 Material evaluation

The material is described along the strategic, tactical, and operational dimensions as outlined in the methodology. The works meeting the inclusion criteria are enlisted along with the use case cluster, the applied research method, and the Computer Classification System level 3 categorization in the table below.

Table 4: Overview of the works meeting the inclusion criteria

Cluster	Publication	Research method (adapted from Spina et al., 2016)	CCS class (ACM, 2012)
Procurement strategy	Veit et al., 2017	Case study	Learning settings
	Abolbashari et al., 2018	Case study	Knowledge representation and reasoning
	Lorin, 1997	Conceptual	Machine learning approaches
	Cheung et al., 2004	Model building	Distributed artificial intelligence
	Choi et al., 2018	Simulation	Knowledge representation and reasoning
Strategic supplier management	Cavalcante et al., 2019	Simulation	Learning paradigms
	Pournader et al., 2019	Case study	Machine learning approaches
	Choy et al., 2002	Case study	Machine learning approaches
Supplier sustainability	Kuo et al., 2010	Model building	Machine learning approaches
Supplier pre-qualification	Choy et al., 2003	Case study	Machine learning approaches
	Lam et al., 2011	Case study	Machine learning approaches
	Wu and Barnes, 2012	Model building	Machine learning approaches
	Plebankiewicz, 2009	Model building	Knowledge representation and reasoning
	Jain et al., 2014	Model building	Learning paradigms
	Khoo et al., 1998	Model building	Knowledge representation and reasoning
Cost analysis	Chou et al., 2015	Case study	Machine learning approaches
	Degraeve et al., 2004	Case study	Knowledge representation and reasoning
	Caputo and Pelagagge, 2008	Model building	Machine learning approaches
Negotiation support	Schulze-Horn et al., 2020	Delphi	Machine learning algorithms
	Carbonneau et al., 2008	Model building	Machine learning approaches
	Matwin, 1989	Model building	Knowledge representation and reasoning
	Sim et al., 2009	Model building	Distributed artificial intelligence
Automated negotiation	Moosmayer et al., 2013	Case study	Machine learning approaches
	Oliver, 1996	Case study	Machine learning approaches
	Baarslag et al., 2017	Conceptual	Distributed artificial intelligence
	Guosheng and Guohong, 2008	Model building	Machine learning approaches
	Lin et al., 2011	Model building	Knowledge representation and reasoning

	Guo et al., 2009	Model building	Machine learning approaches
	Hindriks and Tykhonov, 2008	Model building	Distributed artificial intelligence
	Son et al., 2014	Model building	Knowledge representation and reasoning
Supplier selection	Moghadam et al., 2008	Case study	Control methods
	Hosseini and Barker, 2016	Case study	Knowledge representation and reasoning
	Kashiwagi and Byfield, 2002	Case study	Distributed artificial intelligence
	Wu and Barnes, 2016	Case study	Knowledge representation and reasoning
	Lee and Ou-Yang, 2009	Model building	Machine learning approaches
	Venkatesh et al., 2019	Model building	Machine learning algorithms
	Vahdani et al., 2012	Model building	Machine learning approaches
	Yücenur et al., 2011	Model building	Knowledge representation and reasoning
	Kang et al., 2012	Model building	Learning paradigms
	Luan et al., 2019	Model building	Machine learning approaches
	Ferreira and Borenstein, 2012	Simulation	Knowledge representation and reasoning
Ordering	Faez et al., 2009	Literature review	Machine learning approaches
	Bodaghi et al., 2018	Model building	Knowledge representation and reasoning
Risk monitoring	Nepal and Yadev, 2015	Case study	Knowledge representation and reasoning
Supplier evaluation	Shore and Venkatachalam, 2003	Model building	Knowledge representation and reasoning
	Narasimhan et al., 2001	Model building	Machine learning approaches

These works meeting the inclusion criteria are described in the following sections along the strategic, tactical, and operational levels of procurement with empirical insights from the expert interviews, very recent academic publications as well as relevant popular studies.

2.3.6 Strategic level

Prominent strategic use cases are, for instance, influencing make or buy decisions, accessing supplier innovations, and conducting portfolio analyses that cluster around procurement strategy, strategic supplier management, and supplier sustainability.

Starting with the procurement strategy, an example is the deployment of a fuzzy cognitive map as knowledge representation and reasoning to prioritize requisitions in the public sector in Russia (Choi et al., 2018). The German industrial corporation Siemens built a recommender system for prioritized activities to carry out and learns from the decisions by the team to suggest better actions in the future (Straub, 2019). This could be expanded by utilizing the sourcing planning of different units to propose bundling options across the organization as described in the bundling study in Chapter 3. A prototypical system has been implemented with a multinational manufacturer utilizing an agent-oriented and knowledge-based system as distributed artificial intelligence (Cheung et al., 2004). In general, an intelligent procurement assistant like an enterprise version of ChatGPT could provide a strong value proposition, such as advising the chief procurement officer to structure the organization based on data or supporting commodity managers to decide whether to rely on a single source or employ multiple-supplier strategies. A major strength of AI is dealing with uncertainty and forecasting demand, e.g., through time-series analysis (Seyedan and Mafakheri, 2020). The interviewees highlighted forecasting spanning sales, procurement, and production functions. This could be applied for instance in the aftermarket, to decide which machinery tools should be kept at the supplier side. In addition, Bayesian networks as knowledge representation and reasoning have been applied to procurement performance measurement (Abolbashari et al., 2018). Case-based reasoning systems as machine learning approaches have been applied in various settings improving the effectiveness and efficiency of decision-making (Lorin, 1997). A combination of lean management and machine learning has improved medicine purchasing in a hospital case study (Jordon et al., 2019). The German technology provider Celonis is combining process mining with machine learning, i.e., learning settings for preparing conformance reviews (Veit et al., 2017). This could be applied, e.g., in the auditing of public procurement organizations (Deloitte, 2020). Similarly, automatic process checks can be utilized to systematically scan for patterns that are associated with price cartels for fraud detection (Guida et al., 2023) or more generally process anomalies such as maverick buying or finding bottlenecks in the value chain.

In addition, artificial intelligence and machine learning technologies can be used to visualize and track key performance indicators for instance in management dashboards.

When asked about data and decision-making, expert IX stated: *"We often work with qualitatively bad data and not much data at all. Digitalization must be seen E2E (abbreviated end-to-end), it is not just having an intranet and a laptop instead of a fax machine (...). Often data is collected several times without knowledge from the other silos and with very different approaches and partners."*

As for strategic supplier management, linking production data with the supplier network can be a differentiator for flexible production systems enabling use cases such as automated negotiation of excess demand while ensuring supply. Case-based reasoning systems as machine learning approaches utilize vague and imprecise information when it is necessary to make decisions in situations under high uncertainty in a case study at the Hong Kong subsidiary of the industrial consortium Honeywell (Choy et al., 2002). Spend visibility can be an important tool to connect strategic data on supplier development, tactical data on tendering, and operational data from ordering. Machine learning and simulation can be combined to create digital supply chain twins using learning paradigms (Cavalcante et al., 2019) as in Spreitzenbarth et al. (2021). This concept is an extension of the digital factory, for instance, with purchasing and sales planning connected through demand planning of the production. Natural language processing can be used to augment supply chain maps with supplier information. Data sharing and data integration with supply chain partners may lead to more data with a higher degree of data quality, for instance, through partnerships with key suppliers (Nitsche et al., 2021b; Klee et al., 2023), i.e., an algorithm anonymously collects data to train a common predictive model for better inventory management. Whereby, knowledge sharing and transfer within a value chain network is likewise essential to deal with complexity. Moreover, sentiment analysis can be used to gain more insights into suppliers (Booth and

Sharma, 2019). Finally, in a case study in the banking industry, a slacks-based measure that determines the degree of inefficiency of a decision-making unit relative to a benchmark group has been incorporated into hybrid network data envelopment analysis models as machine learning approaches to examine the impact of outsourcing on organizational performance (Pournader et al., 2019). Hybrid stands for combining different techniques to solve a problem, for example, a data-driven model may be put together with a theoretically derived model. Similar to an open talent community in the area of human resources (Stringer and Rueff, 2014), procurement could provide a platform with matching algorithms where the essential external demands are described in a none-confidential way and suppliers can submit bids especially for regularly purchasing goods and services. This may result in long-term framework contracts enabling the functional departments and relevant stakeholders such as quality, production, and logistics to evaluate their capabilities without the time pressure of a typical sourcing process.

When asked about their experience with AI and ML, expert XIII from Germany stated: *"Currently often proof of concepts only, for instance with image recognition, search algorithms, and text processing. Work with small solutions with exiting technology and successfully build upon it. As an example, there are interesting applications of target automation utilizing benchmarking. Building on this solution, we can we do next with this data and extend this solution. We have about one million general procurement tenders with text data from offers as well as of requirements document, e.g., are there confidential information included, is the specification well enough described, or too specific towards one supplier? Thereby through this German step-by-step approach with incremental steps, you can "take your customer" with you on this journey."*

Thirdly, supplier sustainability is gaining importance as more people consider where the materials originate, e.g., for batteries of electric vehicles or interior leather design. For example, the German automotive manufacturer Porsche introduced a sustainability rating and is using natural language understanding to identify potential violations of sustainability principles at an early stage. In addition, a start-up from Austria named Prewave helps organizations track human rights abuses, corruption, and environmental pollution, not only within direct business partnerships but also at the lower tiers of the supply chain (Gräve, 2021). Also, organizations such as EcoVadis are providing sustainability ratings augmented with artificial intelligence and machine learning technologies (Boute and Udenio, 2021) that may be useful to fulfill regulatory requirements such as supply chain transparency, as mandated for instance by the recent Supply Chain Act in Germany and upcoming European regulation (The Federal Government, 2022). In addition, Dumitrascu et al. (2020) reviewed intelligent performance evaluation systems for sustainable supply chain management across the automotive value chain. Sustainability is a current mega trend, where chief procurement officers seek digital tools to enhance capabilities to meet environmental, social, and governmental objectives (Volkswagen AG, 2021; Bode et al., 2022). In addition, green supplier selection models have been developed, for instance, a neural network combined with data envelopment analysis and analytic network process. These hybrid methods of different machine learning approaches may consider both traditional selection criteria and environmental regulations, as applied in a case study at a global electronics manufacturer (Kuo et al., 2010). Sustainability was one of the use cases with a strong difference in opinion in the interviews. While some see its business value mainly in marketing purposes, others highlight the potential to reduce total costs. Artificial intelligence and machine learning techniques for supplier sustainability is an important topic that needs further research, due to relatively few publications and the current public interest.

2.3.7 Tactical level

Comparatively many publications can be attributed to supplier pre-qualification, cost analysis, negotiation support, automated negotiation, and supplier selection. As pointed out for instance by Loo and Santhiram (2018) and Li et al. (2023), artificial intelligence and machine learning have greatly impacted the procurement process with automation and AI-assisted sourcing decision-making. Earlier surveys such as Tata Consultancy Services (2016) show that these emerging technologies have already been adopted to automate sourcing processes, for instance by recommending new potential suppliers in many public and private organizations worldwide.

Learning paradigms work well for evaluating criteria at the supplier pre-qualification stage (Jain et al., 2014). For instance, fuzzy neural networks as machine learning approaches were built for construction projects in Hong Kong (Lam et al., 2011). The cycle time was reduced by hybrid case-based reasoning and neural networks as machine learning approaches to benchmark potential suppliers (Choy et al., 2003). Pre-qualification with knowledge representation and reasoning makes it possible to admit only viable contractors for tendering considering past performance, key capabilities, and financial standing (Plebankiewicz, 2009). Early research has used a Java template with knowledge representation and reasoning to crawl the web for prospective suppliers to determine if they can supply the requisitions according to the specifications (Khoo et al., 1998). Today, several platform service providers offer data-driven support to identify potential new suppliers through search methodologies, such as Scoutbee. This can be useful to find alternative suppliers that can be built up as a second source, especially in times of high uncertainty, improving supply resilience. In addition, this can help organizations to find niche suppliers, often small- and medium enterprises or also diverse suppliers that are becoming more and more important for public procurement such as in the United States of America (General Services Administration, 2022) but also private organizations such as Google (Belz et al., 2022). However, it is an important management challenge to properly align the organizational objectives and culture around procurement managers of feeling safe to actively use the available technology augmenting their skills and knowledge. For successful pre-qualification of new potential suppliers, it is essential to motivate the entire organization in particular development, production, quality, and logistics to take the risk to qualify a new supplier without being penalized for not previously knowing this supplier in their commodity as their key area of competence. Hybrid machine learning approaches have been applied using fuzzy set theory with radial basis function neural networks to classify potential partners (Wu and Barnes, 2012). The tender design can be pre-configured through natural language understanding of the specifications, i.e., to optimize the bidder's list. This is applied for instance in the Volkswagen Group, which deploys machine learning algorithms to suggest possible suppliers to the buyers (Hülsbömer, 2019).

When asked about their experience with AI and ML, expert XVI stated: *"In practice not many concrete applications have been observed in procurement. There are, however, more and more AI-enabled services, for example, the German start up Scoutbee where AI technology is part of a solution for procurement (...). Other use cases cluster around master data and business logic adaption, e.g., from the brewery business for data quality ("use technology to tidy up the basement")."*

A case study of cost analysis at a German automotive manufacturer demonstrated that regression trees and Bayesian optimization have the potential to lessen the inherent uncertainty associated with supplier selection while making it measurable to some degree within the total cost ownership framework (Spreitzenbarth and Stuckenschmidt, 2021). Similarly, in a recent automotive case study at the German manufacturing group BMW, a comparative study with different cost estimation algorithms was conducted (Bodendorf et al., 2022b). The procurement analytics start-up Arkestro based in the United States of America offers solutions to offer data-driven insights to accurately predict costs to streamline purchasing processes (Arkestro, 2022). This may include the deduction of targets for new parts based on the specific characteristics and could be extended to an autonomous request for information tool. In addition, it may be useful to concentrate on specific aspects as knowledge representation and reasoning, e.g., predicting quality costs (Degraeve et al., 2004). Also, as described in the following chapter, a case study of the bundling problem has been conducted with a German automotive software organization utilizing forward-looking procurement planning data of requisitions to recommend to the buyers potential saving opportunities. Buyers commonly utilize spend analysis as an essential method to proactively identify potential savings, manage supply risks, and optimize their purchasing power (Sammalkorpi and Teppala, 2022). The purpose of spend analysis is to gain insights into past purchasing patterns and generate a forecast of future spending. This is achieved by creating spend cubes, which represent data in a multidimensional cube format, typically organized by suppliers, projects, and categories of goods or services purchased as visualized in Figure 10. To facilitate analysis, operational data is initially extracted, transformed, and loaded into a data warehouse, enabling online analytical processing through user-friendly graphical representations (SAP, 2020; Sammalkorpi and Teppala, 2022). Technology providers like Amazon, Coupa, Jaggaer, SAP, and Sievo often employ recommender systems (Vollmer et al., 2018; Lindsey, 2020; Allal-Chérif et al., 2021) that employ collaborative filtering and content-based filtering techniques to assist industrial buyers in discovering relevant information (Park et al., 2011). For cost analysis, the correct classification from the requisitions, purchasing orders until invoices and payments is essential in order to properly understand the external expenditure of the organization, whereby taxonomies such as ECLASS as a four-tiered classification standard can be utilized (ECLASS e.V. Association, 2022). The utilization of artificial intelligence and machine learning technologies can effectively support procurement controlling and master data management processes. These technologies can aid in tasks such as eliminating duplicate supplier entries, rectifying misspellings, classifying requisitions and invoices, and aggregating spend data from individual group companies into the holding structure (SAP, 2020; Sammalkorpi and Teppala, 2022). This may lead to significant improvements in data quality facilitating other use cases in operations and supply chain management. Furthermore, based on construction project data in Taiwan, neural networks are more reliable compared with regression methods and case-based reasoning as machine learning approaches (Chou et al., 2015). Even if only a small and inaccurate information set is available, machine learning approaches in expert systems can make complex decisions under uncertainty (Caputo and Pelagagge, 2008). Furthermore, neural networks can help designers make decisions early in the development process. As most life cycle cost is defined in the early stages, engineers can substantially reduce the total cost by querying the model with new high-level product attribute data to guide them through the conceptual design at target cost.

When asked about other relevant use cases, expert XVIII from Great Britain stated: *"Cost analysis can also be strategic - as data foundation procurement strategy! For instance, design to cost (...). There is no single solution and prioritization for every organization. In general, prioritize use cases where there is a strong data foundation. Take the biggest cost driver, e.g., construction and installment of cables. And really understand this market through AI utilizing transparency."*

Negotiation support can be provided through the analysis of the spread of offers and an examination of cost breakdowns to determine high-competitive or low-competitive situations. If there is strong competition, an optimized auction setting could be recommended considering the specific circumstances of the tender; if there is not much competition, an in-depth analysis could be initiated supported by human cost engineers with machine learning algorithms (Schulze-Horn et al., 2020). In addition, offers could be generated for the potential suppliers decreasing their opportunity costs including a derived target price to be competitive. Natural language understanding can be applied to scan contracts providing feedback to buyers and legal counsels for contract review and approval processes (Booth and Sharma, 2019), for instance by IBM or Icertis as part of an encompassing contract lifecycle management solution (Guida et al., 2023). Moreover, a virtual version of the salespersons could train buyers, for instance evaluating whether a proposal should be approved or rejected. Bayesian learning and genetic algorithms as distributed artificial intelligence can support negotiations with incomplete information (Sim et al., 2009) and in complex situations, e.g., with knowledge representation and reasoning (Matwin et al., 1989). Opponents' moves can be predicted using neural networks and other machine learning approaches (Carbonneau et al., 2008), for instance for spot buying. The management consultancy BCG described a coaching tool based on machine learning algorithms to support negotiations since experienced buyers use typically a similar set of negotiation tactics, which may not be ideal for each situation estimating that an additional savings of five percent may be feasible if the negotiation is supported by the full range of tactics.

When asked about their technological understanding, expert X said: *"Algorithm development, retrieve data, able to identify cluster and interpret these results to make them useable. As an example, what kind of negotiation should be conducted? An approach could be to recommend an action through the analysis of the spread of offers and cost breakdowns to determine a high or low competitive situation. If high, do that. When low, do that. This could be kind of a "navigation system" for procurement."*

A pilot at the retail chain Walmart of automated negotiation was conducted for minor items achieving savings previously unexploited with start-up Pactum from the United States of America (Kahn, 2021). Traditionally, buyers had to choose where to focus attention to improve outcomes on multiple dimensions with time, budget, and quality factors, which resulted in many smaller requisitions as the long tail are merely, if at all negotiated. Technological tools such as catalogue management systems like Amazon Business or GEP Smart for spot buying of minor goods have been developed to ease this issue for buyers and also internal requestors. Computers that negotiate with distributed artificial intelligence will become indispensable, for instance in smart grids where human negotiation is too slow and expensive (Baarslag et al.,

2017) possibly negotiating in n-dimensions, such as prices, payment and logistics terms as well as quality and temporal factors. Thereby, buyers can focus on oversight and parameter tuning with machine learning approaches (Moosmayer et al., 2013). A hybrid Bayesian fuzzy game has been applied to improve negotiations of construction materials with knowledge representation and reasoning (Son et al., 2014), for instance through fuzzy inference theory using customizable strategies as knowledge representation and reasoning (Lin et al., 2011). Others modeled opponents in multi-issue negotiations with distributed artificial intelligence. The efficiency of multi-issue negotiation thereby depends on the availability and quality of knowledge about the opponents, i.e., how well the preferences and priorities of the other parties are understood (Hindriks and Tykhonov, 2008). However, when computer negotiation is utilized without establishing control mechanisms, it does not bring value per se but may even lead to suppliers increasing prices, if it is not well introduced (Cui et al., 2022a). In general, neural networks as machine learning approaches achieve better results than traditional statistical methods (Oliver, 1996). Yet, they have drawbacks, such as local optima, lack of generalization, and uncontrolled convergence. Support vector machines may overcome these drawbacks in terms of explanatory power with machine learning approaches (Guosheng and Guohong, 2008), which is important to build trust with machine learning approaches (Guo et al., 2009). Also, a consortium of major Japanese industrial, non-governmental, and academic organizations highlights the use case of highly standardized services and for materials buying, because of close to real-time adjustment of the price, delivery date, and quantity for instance in the automotive supply chain (Automated Negotiation SCM Consortium, 2023). Yet, as described in the study on ethical implications of autonomous negotiation agents in Chapter 4, autonomous agents are treated differently by humans and held to a different ethical standard that is likely to change as the technology evolves (Baarslag et al., 2017). For instance, research such as Mell et al. (2020) has shown that some principal organizations prefer that their negotiation agents employ ethically questionable tactics such as withholding information and emotional manipulation. Research in cognitive psychology suggests a common tendency where individuals display reduced ethical conduct when operating through intermediaries, be it human or machine (Mik, 2021). The active consideration of ethical design principles is thereby paramount in the development and operation of autonomous negotiation agents as highlighted in the study described in Chapter 4. Overall, the expert assessment of this use case was divided. While some consider automated negotiation a major step forward, others highlight topics such as supplier innovation, partnership management, and sustainability that are more essential than the mere negotiation of prices and conditions. Ultimately, how is machine negotiation different from human negotiation? It is likely to be faster, more data-driven, and order quantities might be lower with a tendency toward shorter lead times and more suppliers (SAP, 2020). In general, human-machine results are promising (Cui et al., 2022a; Saenz et al., 2022) with a myriad of questions for future research.

Expert XX questioned that *"For automated negotiations, does a machine actually negotiate more often or more strongly than humans."* While a machine can conduct many negotiation rounds, its effectiveness requires human expertise to find and correctly quantify the actual preferences of the business function to set the objective function. Expert IV contrasted that while this may be true, it is not necessary for all types of negotiations: *"An interesting use case is automated negotiation (especially) automated C-rated (smaller requisitions as the long tale of spend) requisitions that have previously not been negotiated."*

Bayesian networks can provide resilience-based supplier selection frameworks as knowledge representation and reasoning based on performance indicators such as delivery robustness, innovation, total costs, quality of products, and sustainability aspects (Hosseini and Barker, 2016). Fuzzy-Bayesian supplier selection has been applied as knowledge representation and reasoning (Ferreira and Borenstein, 2012), as well as a neuro-fuzzy case study in the cosmetic industry with machine learning approaches (Vahdani et al., 2012), in combination with optimizing inventory lot sizing using control methods (Moghadam et al., 2008) and humanitarian operations with machine learning algorithms (Venkatesh et al., 2019). This could be used, for instance, to optimize volume allocation in multi-source nominations. These models have been applied under a fuzzy environment to evaluate decision criteria and with knowledge representation and reasoning (Yücenur et al., 2011). Since it is difficult for decision-makers to provide exact values for these input factors, fuzzy analytic networks as learning paradigms may calculate the weights of each factor, e.g., in the packaging industry case study in Taiwan (Kang et al., 2012). Partner selection is a potential lever in improving the sustainability of the supply chain, this has been applied in reverse logistic centers for green supply chains in Chinese manufacturing companies integrating fuzzy inference theory and artificial immune optimization technology as knowledge representation and reasoning (Wu and Barnes, 2016). Hybrid methods incorporate multiple techniques to select suppliers by calculating a score to account for qualitative and quantitative factors. A hybrid genetic algorithm with ant colony optimization has been applied with a multi-objective linear programming model considering product quality, price, and delivery capacity as machine learning approaches (Luan et al., 2019). Neural networks can be used to forecast supplier bid prices and to estimate the possibility of a successful deal as machine learning approaches (Lee and Ou-Yang, 2009). The Chinese information technology corporation Alibaba has initiated an automatic request for quotation as a service with integrated chatbot features to automate communications (Cui et al., 2022a). In the State of Utah in the United States of America, distributed artificial intelligence was applied to support the selection process of construction suppliers minimizing subjectivity bias in the decision-making (Kashiwagi and Byfield, 2002). The Singaporean government applies search methodologies and control methods to prevent procurement fraud. Great Britain has published guidelines for the regulation of AI and ML technologies in public procurement (Deloitte, 2020) highlighting the benefits but also the need for control. Potential applications in public procurement include analysis of government spending and stakeholder sentiments, identification of corruption, contract preparation and management, and further automation of procurement-related tasks (Guida et al., 2023). So far, no corporate purchasing guideline for AI and ML in a private organization has been identified. Yet, guidelines such as by the international organization World Economic Forum (2019) advocate the potential of procurement to effectively act as a gatekeeper in particular by setting privacy and information security standards and making ethical considerations part of the offer evaluation criteria. Overall, supplier selection received the highest research attention of the clusters. However, based on the expert assessment, it may be advisable to focus research attention also on other use cases, for instance in the operative area.

2.3.8 Operational level

Many expect AI and ML to be implemented in operative areas first (Vollmer et al., 2018; Ziegler et al., 2019; Chui et al., 2022; Mittal et al., 2022), however, there are few works on operational use cases. The identified operational publications mainly cluster around risk monitoring, ordering, and supplier evaluation described in the following.

For risk monitoring, the German start-up Riskmethods has developed a risk monitoring tool (Guida et al., 2023). Benefits are, for example, the ability to act quickly based on keyword and location searches, particularly with complex sub-supplier management such as for semiconductors. Supplier selection and risk management are inextricably linked, e.g., failure modes and effects analysis from the field of reliability engineering and Bayesian belief networks as knowledge representation and reasoning has been combined to quantify risk factors in a case study of a chemical distributor in the United States of America (Nepal and Yadev, 2015). In addition, the technology consultancy Accenture has built supply chain risk cockpits to assess supplier sides individually with a risk score based on regional factors such as pandemic lockdowns (Papa et al., 2019). An emerging concept is the supply chain control tower, whereby the machine learning algorithms are often combined with simulation to expand resilience by increasing supply chain transparency (Schuh et al., 2022). External data could help to anticipate delays in supplier production cycles as well as sudden changes in the raw materials market or regulations. However, it should be linked to internal data and be embedded in the end-to-end processes (Klee et al., 2023). Lastly, compliance reviews, patent reviews, and fraud detection round up the potential risk monitoring toolbox.

When asked about their experience with AI and ML, expert III stated: *"Use case evaluation for procurement internally and with IT systems providers. An example is news crawling and social media analysis. Risk management use cases seem very attractive, for instance using Google GDELT (standing for Global Database of Events, Language, and Tone) with meta-data of billions of historic and current news sources. Also interesting are predictive use cases for pricing. Yet first we must lay a solid data analytics foundation and later add further analytics capabilities. There must be a descent data quality!"*

Chatbots can help not only internal requestors to navigate through the ordering process as part of a guided buying information technology system but also answer standard questions from the supply base, e.g., by the start-up Botfriends from Germany. In addition, supplier onboarding, capacity planning, and purchasing controlling could be supported in a similar way through machine learning approaches (Faez et al., 2009). Siemens is using a bot for logistics services that finds the contracted rate, provides the next best available rate, or the option to start a new request for quotation (Straub, 2019). The United States Airforce is working with IBM to guide potential vendors through the about two thousand pages of Federal Acquisition Regulation to receive more and better offers (Deloitte, 2020). Also, the automotive supplier Hella employed the historical records of goods received, purchasing and logistics details as well as supplier and material master data to predict the monthly reliability of delivery quantities

(Huang, 2020). Order management may be connected to supplier sustainability, e.g., by utilizing the geolocations of trucks through link connection, it is technically possible to associate suppliers with deforestation or with sub-suppliers with an uncertain reputation. For catalog management, text analysis can be conducted for special requisitions with automatic expansion. Moreover, it can be predicted when the framework contract is consumed and timely triggers expansion. Capacity and contract data can be matched with ordering data comparing prediction and actual, e.g., to provide actionable recommendations to reach volume bonuses through knowledge representation and reasoning (Bodaghi et al., 2018).

When asked about their experience with AI and ML, expert XIV from the United States of America stated: *"Bots take over the standard jobs, there is potential for either less buyers or more time for strategic consideration with negotiation of long-term contracts, cost reductions, and relationship building. A good example is contract comparison in different formats with versions management. Another example are standard goods with catalogues for self-service of requestors (just like Amazon "hands off catalogue") where buyers can support "hands on catalogue" e.g., for special goods."*

Supplier evaluation can improve results when performance history, geography, and price are considered. Supplier ratings for instance from engineering, quality, and logistics may be aggregated and proposed automatically by machine learning approaches (Narasimhan et al., 2001). Fuzzy logic in combination with the analytical hierarchy process has been applied since it explicitly handles vague, ambiguous, and imprecise data by knowledge representation and reasoning (Shore and Venkatachalam, 2003). Moreover, supplier quality management could benefit from analyzing defects in the inbound quality control to deduct process and product improvements while reducing quality costs. For instance, Siemens Gamesa has collaborated with its Japanese supplier Fujitsu on a common innovation based on deep learning image and signal processing to improve safety checks on installed wind turbines (Schuh et al., 2022).

2.4 Results and discussion

Finally, to answer the third research about gaps in the literature and potential directions for future research and applications, the research activity from the material evaluation is matched with the results of the interviews. The works meeting the inclusion criteria on the left side are matched with the derived cluster from the literature in the middle of the figure below as well as the three most highly rated clusters from the expert interviews.

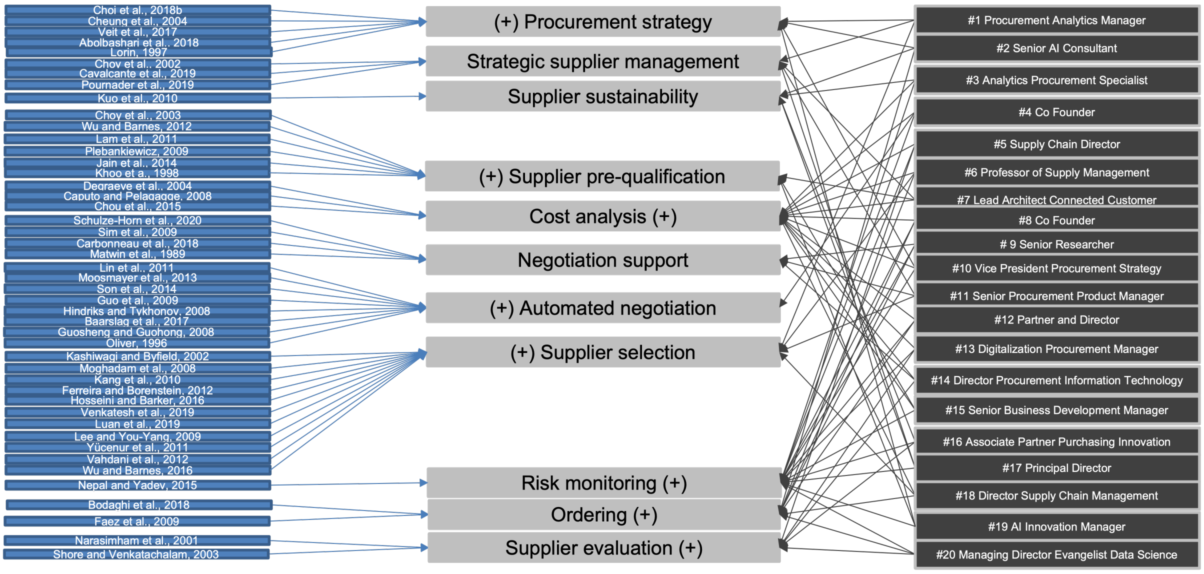

Figure 8: Mapping of the literature, clusters, and expert interviews

As shown visually above, there seems to be a mismatch between the research activities with a focus on automated negotiation and supplier selection and the assessment of the experts that overall see more highly value of AI and ML in the operational area of procurement. Next, the research activity has been calculated by multiplying the number of publications of the use case cluster with the number of citations.

Equation 1: Research activity of the use case clusters

$$\forall \text{ clusters c and publications p: number of } p * \sum_{p=1}^{q} citations\ of\ p$$

The aggregated expert assessment of each use case cluster can be calculated by the sub-dimensions of the business value and ease of implementation.

Equation 2: Attractiveness of the use case clusters

$$\forall\ clusters\ c\ and\ interviews\ v: \frac{(financial+customer+strategic)+(input+knowhow+change)}{6}$$

The mean of Equation 1 and Equation 2 above is taken respectively and for each cluster, the deviation from the mean μ is calculated in terms of their standard deviation σ.

Equation 3: Calculating the standard deviation for all clusters

$$\forall\ clusters\ \text{c}: f(c) - f(\mu)\frac{f(c) - \mu}{\sigma}$$

This relative measurement allows for comparing the clusters for their present research activity in blue coloring and their assessment in the interviews in orange coloring visualized in the figure below.

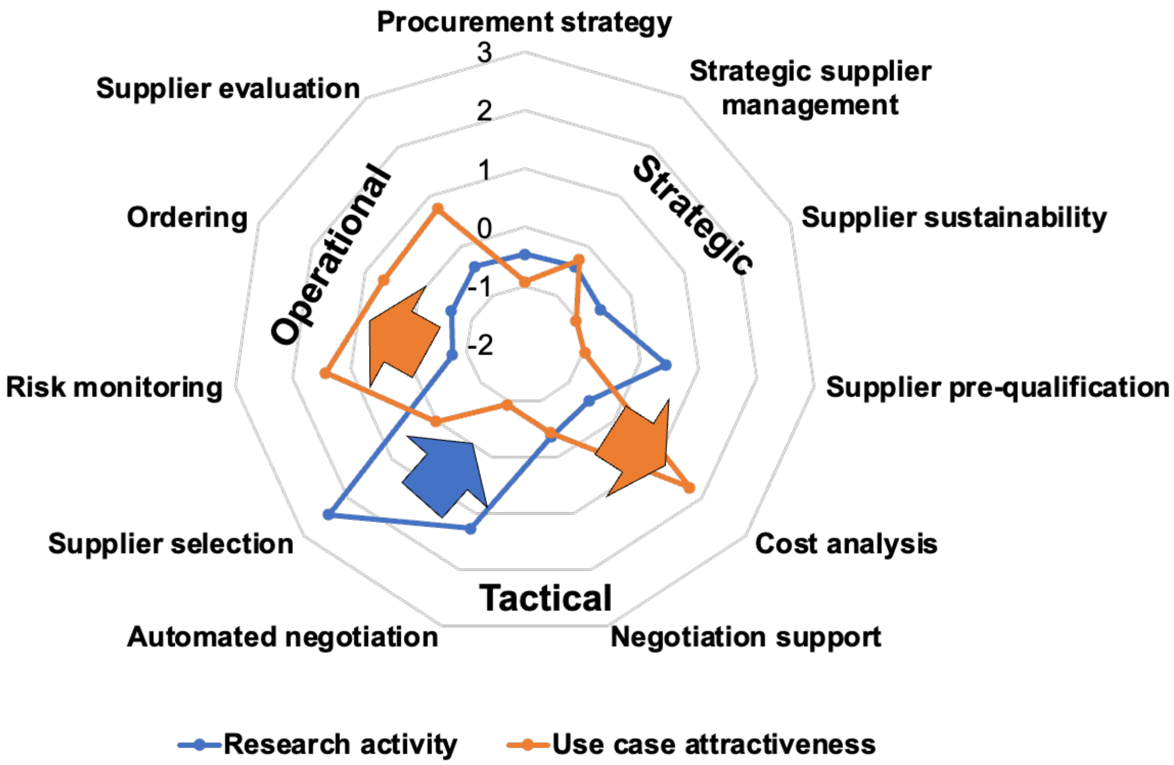

Figure 9: Comparing research activity and cluster attractiveness

Based on this empirical analysis the most attractive clusters are cost analysis and operational use cases grouped in risk monitoring, ordering, and supplier evaluation. Furthermore, practical reports from supply chain consultancies and industry associations highlight that although procurement has evolved to encompass strategic objectives like sustainability and innovation, shareholders and the management board still primarily emphasize its crucial role in cost management for the overall success of the organization (Kearney, 2021; Bode et al., 2022). As an example, Burger et al. (2023) described four case studies that be assigned to the clusters ordering, supplier pre-qualification, risk monitoring, and cost analysis. Still, after conducting and analyzing the interviews the classification of risk monitoring could have been set on the strategic level of procurement.

It is compelling that some clusters are not yet well researched if at all described by popular publications. This restricts the extent of a review; however, this limitation is likely to be overcome with more research and implementation. For instance, similarity analysis of parts based on specifications and technical drawings could yield substantial savings due to the reduction of variations and complexity. Moreover, linking supplier data to real-time production demands could lead to productivity gains by connecting capacity management with automated negotiation and risk monitoring. Next to replication studies, meta-studies on the clusters, and concrete applications, the following questions for future research were derived by discussions among the research team of the literature and the expert interviews in a brainstorming session that have further detailed in the section research outlook of this dissertation:

- What is the impact of AI and ML applications on business performance in PSM?
- How does procurement compare in the technology adoption with other functional areas, i.e., the negotiation partners in sales and marketing functions, and why?
- How can supply chain integration further be supported by AI and ML?
- Which ethical aspects should be considered for AI and ML in procurement?

- Which regulations should be introduced regarding procuring AI and ML technologies and in terms of applications in procurement organizations?

Due to its responsibility to own the relationship with the suppliers, procurement is in a unique position in the supply chain to exploit this data potential (Nitsche et al., 2021b; Wamba et al., 2021; Roy, 2022). For instance, in the automotive industry, procurement typically could access a variety of information concerning supply chain partners, prices and conditions, delivery reliability, and specifications (Hofmann et al., 2017). Data of related functions, i.e., from marketing, controlling, engineering, and quality could be cross-functionally shared through a standardized data structure such as a data lake. However, across all industries, there is still a low usage of advanced procurement analytics, whereby data integrity and quality issues are hindering performance increases (Handfield et al., 2019).

When asked about process data, expert III stated: *"Data is the new oil for corporations worldwide. I often deal with structured data, e.g., from procure to pay and all kinds of data from procurement. It would be great to process data E2E in the supply chain, e.g., production supplier with tooling overall equipment effectiveness (supplier integration). This could enable further use cases, e.g., predicative maintenance or for switching production capacities in a switch manner. Thereby, AI can clean and sort data."*

Choosing a technological solution is an important decision because of the opportunity to tap into an ecosystem. When considering whether to build proprietary applications or purchase existing solutions, there is a trend toward buying rather than making them from scratch. This is consistent with the aforementioned Deloitte survey, whereby most organizations acquire solutions rather than building them in-house (Mittal et al., 2022) for instance through presumably plug-and-play software as a service offerings. However, as pointed out in the methodological section, the digital transformation is not an end but must provide value to the organization to justify the investment. Therefore, the technology adoption must fit with the dynamic capabilities needs of the organization (Teece et al., 1997).

Vice-versa managerial decision-makers need to ask the reverse question, of the direct and indirect consequences of not engaging with this emerging technology, particularly for managing data of the supply chain network and generally supplier-buyer relationships. Claims by information technology providers of simple solutions through application programming interfaces to established systems such as ERP must be individually analyzed considering the often highly customized information systems landscape with legacy systems. Several experts stressed that the integration complexity is often underestimated in practice. In addition, especially AI and ML technologies must be accompanied by stringent change management including training and if feasible, provide the opportunity to actively take part in the model training following the findings of Dietvorst et al. (2018).

Chief procurement officers may ask the question of what types of data need to be systematically gathered for AI and ML technologies and promote data-driven decisions, thereby building trust in the data and algorithms when they are used (Schoenherr and Speier-Pero, 2015; Nguyen et al., 2018) to augment the skills of buyers. The technology provider Amazon pointed out that "*Procurement is rich with data, and that means AI and machine learning can be especially impactful in helping businesses save money, manage supplier risk, and meet customer demand with speed and agility. But some companies, especially those that are smaller or tech-averse, believe AI-powered procurement is out of reach*" (Lindsey, 2020).

It is thereby important to consider, where and how the data is gathered and processed in order to facilitate current and further use cases (Herold et al., 2022). Especially experts from large public and private organizations pointed out that it is essential to have a holistic view of data processing needs and capabilities to enable cross-functional usage instead of allowing data silos to exist. Considering decision-making echelon models such as Boute and Van Miegham

(2021), the expert interviews have shown that some organizations only want the AI and ML systems to support human decision-making for instance through recommendation systems that augment the skills of buyers as in the bundling study in Chapter 3, others are open for instance to autonomous negotiation agents described in Chapter 4 that can take their own decision whereby humans focus on parameter tuning and oversight (Moosmayer et al., 2013).

When asked what leading AI and ML technology organizations do differently than others, expert II stated: *“More pragmatic, different thinking! Direct and indirect savings also with a long-term perspective and a clear focus on data quality.”* And expert X added: *“Other organizations such as Google must value flexibility, and therefore have adopted a very different mindset. For our organization, there is a classical efficiency focus with strong project steering and clear business plans (...). Yet, I believe that the mechanism of the past does not necessary work in the future, and we must now set a solid foundation of it!”*

According to Detlef Schultz, Chairman of Vodafone Procurement Company within the telecommunication service group, "*artificial intelligence will help the category managers grasp the information they need to do their job*” (Marlinghaus, 2018). Generally, it may be advisable to apply these emerging technologies not for incremental improvements of already highly optimized processes in procurement organizations, but for new challenges such as sustainability that are prone to data-driven decision-making, such as risk management and negotiation. Currently, there are often proof of concepts only that either do not scale or do not fit well enough for practical application in the field. Moreover, many of the identified use case clusters in the literature lie at the internal and external purchasing-marketing. Thus, more research should be conducted on how to enable the cross-functional potential such as Nitsche et al. (2021b), Spreitzenbarth et al. (2022a), Burger et al. (2023) and also in the following studies described in this dissertation in Chapter 3 and Chapter 4.

Furthermore, the former leader of the AI research groups at Google and Baidu Andrew Ng has emphasized the advantages of beginning with small-scale applications: *"My advice for executives, in any industry, is to start small. The first step to building an AI strategy, (...) is to choose one to two company-level pilot AI projects. These projects will help your company gain momentum and gain firsthand knowledge of what it takes to build an AI product"* (Ng, 2019). One of the primary implementation drivers that was empathized by the interviewed experts was the quality of decisions in combination with scalability, e.g., reviewing several million contracts quickly and consistently. An often-mentioned common pitfall was data generation with unequal probabilities of inclusion and opportunity structures. In addition, the talent gap might hinder the potential to be realized as well as legal and ethical aspects. While training the workforce was considered important to enable buyers and their stakeholders within and outside the organization to use the technology, most experts agreed that new talent must be hired in order to introduce and manage the emerging technologies.

When asked what technology champions to do differently, expert VI from the Netherlands stated: *"Better marketing. IT giants have real-time big data in contract to classical manufacturing companies. Therefore, it is difficult to compare. Learning works better with large amounts of data. Now what is big data in fact? Hundred cases, ten thousand? Often in procurement and B2B not enough data, B2C has more data in an hour than a typical manufacturing procurement organization in a whole year."*

Thereby, one must consider each problem individually, not looking with the "AI hammer" for problems that seem similar. Transparency into the metrics and data remains critical, i.e., data should be provided on how vendors were selected, how data security is ensured, and how the algorithms were trained (Ziegler et al., 2019; SAP, 2020). One potential approach is to focus on the major cost drivers, e.g., for telecommunications installment of cables - understand trends and make predictions based on data - deeply understanding this supply market through artificial intelligence and machine learning.

2.5 Conclusion

This inductive review offers an overview of artificial intelligence and machine learning in procurement with 46 works that have been iteratively assigned to 11 use case clusters. During the systematic search, it became apparent that a practitioner's perspective is essential in this early phase of the adoption of these emerging technologies. In addition, during the keyword search, the researchers identified that there is a need to use an established ontology for the precise wording of the applied techniques. Comparing literature with the expert assessment, alignment but also mismatch was apparent as visualized in Figure 9. The cluster cost analysis deserves higher research attention while other use case clusters may be deemphasized such as building another model for supplier selection based on fuzzy logic. For some clusters, the interviewed experts had divergent opinions, such as on applications to strengthen supplier sustainability or use negotiation bots. Moreover, there seems to be a gap in the literature on artificial intelligence in the operational area of procurement, which many believe to be first considered due to data availability.

2.5.1 Theoretical contributions

For the first research question, the developed classification framework illustrated in Figure 7 combines commonly accepted models from operations management and computer science literature into a unified framework that enables a deeper understanding of AI and ML in PSM. Methodologically, content analysis based on Mayring (2014) was extended by utilizing interviews to enrich the material evaluation to include a practitioner's point of view in the analysis of the literature. In addition, this is the first known review to apply the Computer Classification System and utilize the related ACM Guide to Computing Literature to strengthen the interpretation and assessment of the coding, in particular what types of technologies have been applied. This work started with the umbrella term "AI" in mind, but for clarity in the discussion e.g., if an algorithm is artificial intelligence, machine learning, or another kind of computational method, it was decided to choose the de-facto standard from computer science as they deemed the various understandings confusing and not useful to conduct a structured literature review.

Many of the articles meeting the inclusion criteria can thereby be attributed to machine learning with about sixty percent of publications and citations while some classes of artificial intelligence have been seldom applied so far as illustrated in Figure 9, i.e., planning and scheduling, search methodologies, and computer vision. As described in Table 2, most works do not explicitly mention theories, yet some works are based on fuzzy logic, transaction cost economics, and game theory. In addition, some works distinctly focus on concrete applications in manufacturing, transportation, and construction but most works are rather general and not directed toward the particulars of specific uses cases or industries.

The major works identified in the literature review were mainly published in technical journals and conferences, only three of the 46 publications were published in a major journal with an emphasis on procurement, namely the Journal of Supply Chain Management. This is reflected in Figure 5 which summarizes the publication outlets of the works meeting the inclusion criteria of the review. Schoenherr and Tummala (2007) conducted a review of electronic procurement in general with 157 articles in over 80 publication outlets, for instance, in Supply Chain Management: An International Journal. Similarly, Nguyen et al. (2018) identified 88 papers on the encompassing theme of big data analytics in supply chain management in 46 different journals. Based on the results of this literature review, it appears that the finding still holds, which may contribute that there is not yet a common wording basis for the successful digitalization of procurement organizations. The PRISMA statement in

Figure 3 thereby provides a useful overview of the research methodology. Therefore, this work as well as the dissertation in general intends to encourage researchers to submit manuscripts to journals specifically focused on purchasing and supply management to disseminate knowledge in this field and thereby create a stronger basis of common terminology and definitions.

2.5.2 Practical implications

Regarding the second research question, having both the domain knowledge and the technology toolbox will be an important skill set for future buyers. Presently, many existing solutions are limited to proof of concepts that either lack scalability or fail to sufficiently align with practical applications in the field. Chief procurement officers must be more patient and allow for more trial and error. Again and again, there is close to no useable data, therefore it is paramount to start now to lay the foundation to profit in the future, where the following chapter may provide ideas of how to invest in people, data, and technology based on a comparison between the technological adoption of purchasing with marketing and sales.

In addition, an important consideration is to align guiding purchasing principles, especially for public procurement of intelligent systems such as in Great Britain that is highlighting the benefits but also the need for control. Policies might be enacted on how these systems should be designed to profit society, partners and suppliers and thereby influencing the further development of these technologies requiring more research. Moreover, this review calls attention to relevant questions of ethical implications at the buyer-supplier interface and its impact on relationships, power balance, and profits. Furthermore, the insights from literature and interviews may guide procurement executives in their transformation toward procurement 4.0 to better understand the dynamic capabilities needed to successfully steer the organization.

2.5.3 Limitations and future research

As for the third research question, matching the literature and the empirical assessment of the expert interviews the cluster cost analysis deserves higher research attention. Furthermore, the result of the comparative analysis suggests deemphasizing AI and ML research on supplier selection, which is currently the strongest cluster. In addition, sustainability was one of the clusters with a strong difference in opinion in the assessment. Due to relatively little previous research and the current general interest, AI and ML for supplier sustainability is a relevant area for future research. Another cluster with a divergence in opinion was automated negotiation, which some rate as highly important and others as not so relevant as especially essential negotiations are not likely to be fully automated soon.

Future research on artificial intelligence and machine learning in purchasing and supply management could focus on the perspective of the suppliers - following the general call for more research from the supply side as outlined in the recent editorial of the Journal of Purchasing and Supply Management as an opportunity for business-not-as-usual research in procurement In addition, it would be interesting to consider the diverse views such as from the requestors of the buying organizations as well as external stakeholders such as information technology providers, regulatory agencies, and the marketing side.

Moreover, it could have been less work to straight forward assign the identified major works of artificial intelligence and machine learning in procurement to an established framework, such as the Extended Purchasing Process illustrated in Figure 4 instead of searching for common themes loosely tied to it as conducted retrospectively in Figure 19 based on Spina (2008) and Guida et al. (2023). In addition, the classification of risk monitoring after conducting and analyzing the interviews could have been set on the strategic level of procurement and the use case cluster automated negotiation can be described more precisely with the term autonomous negotiation.

Lastly, as the keyword search did not lead to sufficient results, an extensive snowballing search had to be conducted in this early maturity stage. Four commonly used databases with different keywords were explored to reduce possible bias; yet, for instance, Web of Science, Scopus, CiteSeerX, and the ACM Digital Library itself might have added more to the search. This could be due to still early maturation phase with further research and implementations using more consistent wording, for example by utilizing ontologies such as the Computing Classification System. In addition, a literature review based on natural language processing could yield interesting results when a higher level of maturity has been reached. In the research outlook of this dissertation, a literature review based on the CCS classification and the whole spectrum of the SCOR model is proposed to conduct a systematic analysis of artificial intelligence in operations and supply chain management illustrated in Figure 20.

Chapter 3 Designing an AI decision support requisition bundler

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Following the design science methodology, an artifact of a recommender system has iteratively been created to find a novel approach to the bundling problem in order to generate data-driven insights identifying savings potentials across the organization. In this study, a concept that has been implemented in business-to-business marketing at IBM is taken over to procurement in the automotive industry. Thereby, this work builds on information processing theory to utilize artificial intelligence technologies, i.e., natural language processing and supervised learning to augment the skills of buyers through a recommender system, whereby design principles were deducted for technology providers and procurement organizations in private and public settings.

Overall, Mini Batch K-means was the most performative model among the selected clustering algorithms. By actively making use of purchasing requisition data typically available in enterprise resource planning systems, the bundling generator can lead to significant improvements in strategic planning and commodity management resulting in better utilization of buyer's capacities, tender designs, and thus its value contribution by AI-driven decision sciences in the transformation toward industry 4.0. The empirical study contributes to the literature on bundling and spend analysis, which has predominantly relied on historical data to infer future cost potentials. By incorporating requisition data, which poses inherent challenges of precision and information-richness, this work expands the traditional approach with a forward-looking perspective.

3.1 Introduction

Public and private organizations worldwide across all sectors of the economy are profoundly impacted by digital technologies, for instance the automotive industry (Dremel et al., 2017). Manufacturers and suppliers have to fundamentally transform their organizational structures and business processes to make evidence-based decisions toward the vision of industry 4.0 (Hofmann et al., 2017). Emerging technologies such as artificial intelligence enhance the availability to analyze internal and external information along the supply chain (Handfield et al., 2019; Nitsche et al., 2021a). Thus, there is a need for comprehensive industry case insights about artificial intelligence for relevant decision problems in managing supply chains (Wamba et al., 2021). Recent work highlight the value of AI-driven decision sciences in particular for cost analysis such as the systematic analysis of the literature in Chapter 2, Guida et al. (2023), or Burger et al. (2023). In addition, practical reports by supply chain consultancies and industry associations point out that while the role of procurement has changed toward a more strategic role such as for sustainability and innovation, the shareholders and the board of management still consider cost management as its most important contribution to the overall success of the organization (Kearney, 2021; Bode et al., 2022).

Analytics can provide competitive advantages along the supply chain management decision spectrum (Sanders, 2016). As pointed out in a recent call for papers of Decision Sciences, the AI-driven decision-making environment will become more complex, which raises pitfalls and variability for managerial decision-makers (Li et al., 2023). For instance, AI impact procurement decision-making through automation and augmentation (Cui et al., 2022a). During exchanges with buyers and their key stakeholders in a major automotive original manufacturing group, the bundling problem was thus chosen as a lever to identify further cost saving potentials across the diverse and complex organization combining the strengths of expert buyers with AI for data-driven decision-making. The research was therefore collaboratively set up in 2021 as a strategic cost initiative in the midst of the COVID pandemic and concluded in mid-2022.

Bundling similar requirements together is a key challenge of industrial organization, i.e., for procurement to increase its value proposition by combining demands across time, facilities, geographical regions, products, and divisions (Monczka et al., 2020). In this study, bundling is understood that buying organizations may aggregate two or more products or services in a request for quotation or joint negotiation. While demand forecasting is already widely used throughout the organization, research and practice on purchasing bundling decisions and generally spend analysis have mostly looked backward utilizing relatively precise spending data from orders and invoices but leaving out the possibility to expand the information basis with more uncertain future purchasing requisitions (Schoenherr and Mabert, 2006; Ozkul et al., 2012). In addition, during discussions with established and emerging providers in order to better understand the general client's needs, status quo and roadmap, no technological solution has been identified, which can readily process and analyze such data.

To close his theoretical and practical gap, this work builds on a study in business-to-business (B2B) marketing by Vlachos et al. (2016), where a recommender tool was created to support the salesforce of the information technology corporation IBM to identify cross-customer and cross-product opportunities by finding commonalities between requirements of B2B customers in a similar way as for industrial buyers in this work. This led to the research question: **How to design an information system that supports buyers to identify further saving potentials by bundling requisitions?** It is a relevant interdisciplinary problem since for example, a typical Ford passenger vehicle is composed of circa 40,000 parts supplied by 1,200 direct business partners (Schuh et al., 2022), or a global industrial organization such as the Volkswagen Group is managing an external annual spend of over 100 billion euro (Volkswagen AG, 2021).

The research shows how decision-makers can find cost-saving opportunities through AI-powered bundling analysis, despite considerable uncertainty based on a few essential attributes. While creating performative algorithms built on so-called little data used to be a major limitation of artificial intelligence in the past, literature (Qi and Luo, 2020; Russell and Norvig, 2020) as well as this empirical research indicates that this assertion may no longer hold true. Particularly relevant for enterprise resource planning and spend analysis providers, this study describes and motivates the business opportunity to expand the basis for bundling decision analysis with requisition data. Thereby, Mini Batch K-means was the most performative model based on the expert assessment by the buyers of the focal organization with the analysis of the cluster characteristics Also, the results may be transferable to bundling problems in neighboring operations and supply chain management areas such as production and logistics, service management, and industrial marketing. The work is thus contributing to how AI-driven decision sciences can increase operational performance, especially to the current discussion of automation versus augmentation of artificial intelligence in management research (Raisch and Krakowski, 2021).

The remainder of this paper is composed of the methodology with the design science approach and information processing theory, an overview of the case study, and the algorithms. This is followed by the review of the literature on AI in B2B contexts, the bundling problem and spend analysis, and their decision support systems. Then, the results are discussed along the stages of gathering data, processing models, and communicating results with the community. Finally, conclusions are drawn, and limitations with future research opportunities are outlined.

3.2 Material and methods

The developed artifact was created based on the design science methodology following Peffers et al. (2007) to support the focal organization driving down material and service costs by proposing possible bundles cross-functional, cross-supplier, and cross-category based on real requisition data from an ERP system. Through the interactions with the focal company and information technology providers, the research design of an in-depth case study based on information processing theory gradually emerged. Therefore, requirements for potential solutions have been collected with buyers and their key stakeholders against which the developed artifact can collaboratively be evaluated to deduct design principles (Galbraith, 2014). This is essential to generalize the results that may extend current technological solutions, especially in capital-intensive settings and complex organizations with a large degree of external expenditures considering requisition data adjunct to traditional historical analysis.

For the empirical identification of saving potentials, data can be analyzed across the dimensions of commodity, functional, and supplier illustrated by different colorings below with a one-dimensional example each based on spend cubes typically employed by spend analysis tools (Sammalkorpi and Teppala, 2022) further discussed in the review of the literature.

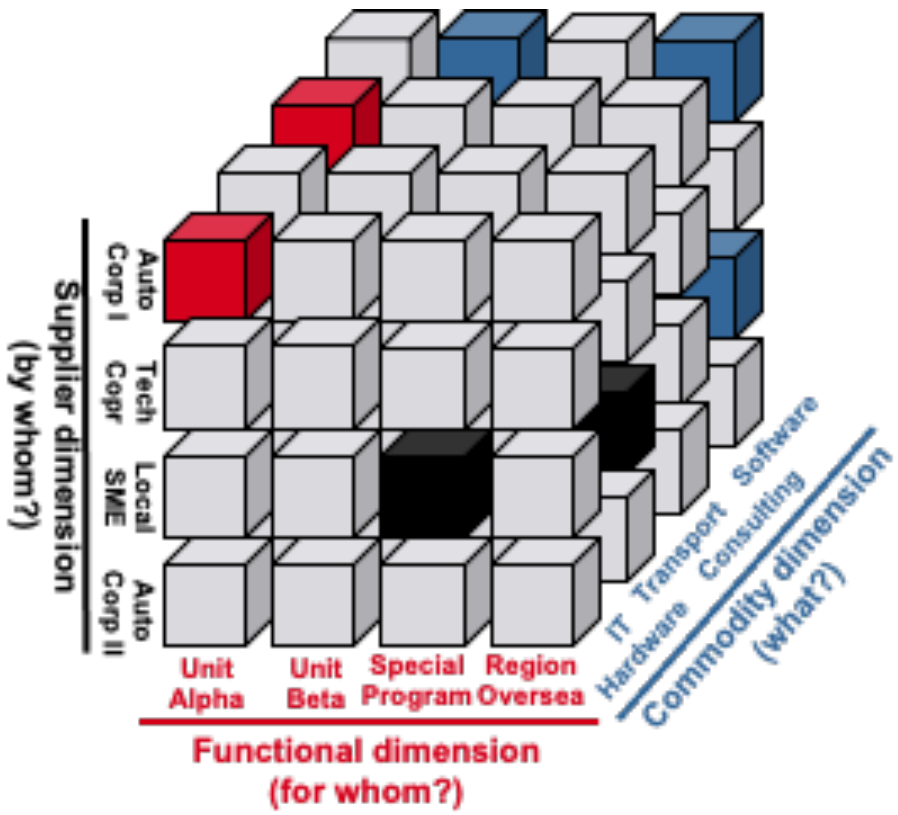

Figure 10: Bundling generator as a three-dimensional cube

The artifact takes as input data of to be purchased goods and services across the organization, generates and ranks options to bundle similar requisitions, and continuously learns through feedback. As graphically represented above, there are several ways to identify potential savings through bundling. For instance, considering the requisitions of Unit Alpha, there is a joint supplier Auto Corp I for the components IT Hardware and Consulting, where a joint negotiation could be conducted. Secondly, focusing on the supplier dimension, awards Local SME are pending for Special Program of IT Hardware and for Region Oversea of Transport that may be negotiated together, if the respective buyers of the tenders are aware of it. Finally, considering the commodity Software, there is possibly a common supplier Auto Corp I for two requisitions that might be bundled in a common tender increasing the size of the sourcing, and thus usually the complexity but also the attractiveness to the supply base (Schoenherr and Mabert, 2006; Ozkul et al., 2012).

3.2.1 Theoretical background

As pointed out for instance by Stange et al. (2022), design science research in operations and supply chain management is still underrepresented but has recently gained momentum. It is a problem-solving paradigm that offers new theoretical justifications and strives to advance knowledge by creating artifacts that tackle pertinent issues and improve the environment in which they are implemented (Gregor and Hevner, 2013). Knowledge from one field can be extended or refined so that it can be utilized in different application areas (Eisenhardt, 1989) like in this research from the field of industrial marketing to procurement.

The design science process is composed of six activities illustrated in the figure below similar to Figure 15 in the following chapter. The first activity involves identifying the problem and establishing the need for a solution. The second activity is to specify the objectives of the investigation. The third is centered on the creation of artifacts, which can be in the form of constructs, models, or methods. The fourth requires the utilization of instantiations to solve the problem. The fifth involves evaluating the solution by comparing the objectives with the outcomes obtained through the practical use of the design artifact. Finally, the sixth activity entails communicating the problem as well as the developed artifact and its value (Gregor and Hevner, 2013).

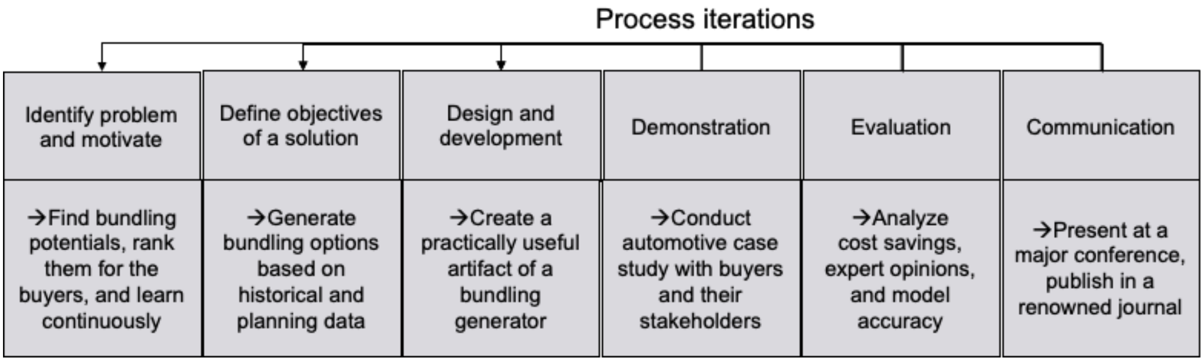

Figure 11: Design science (own illustration based on Peffers et al., 2007)

According to information processing theory, organizations adopt information-processing activities that are best suited to the type and amount of asymmetry they encounter. These activities include gathering, processing, and communicating information to address uncertainty which is characterized by a lack of information, and equivocality which is characterized by ambiguity (Bode et al., 2011). To cope with increased information needs and asymmetry, organizations typically rely on two strategies. The first strategy involves organizing buffers to reduce the impact, while the second involves designing structural mechanisms to enhance the flow of information (Galbraith, 2014). The goal of this work is to contribute to the latter strategy.

Alternatively, sociotechnical systems theory could be applied, as humans interact with an information system. Yet, information processing theory was found more applicable to analyze the status quo in the focal organization as well as design and then evaluate the developed artifact, systematically deducting design principles from it for generalizing the results. As the co-founder of the analytics provider Sievo, Sammeli Sammalkorpi pointed out: "*The more you use data, the better it will get. So, I would argue that the right way to deal with* *the data quality problem is to take the data you have and use it for analytics. You will get feedback from end users and be able to establish feedback loops*" (Ideson, 2021).

3.2.2 Case study approach

The case organization was recently established by merging units across the global group with a newly created purchasing division, which is organized into several teams that are managing an annual spend of over three billion euro and has already introduced a unified ERP system. Its primary objective is to develop and operate a uniform vehicle operating system architecture. Consequently, procurement is faced with a diverse array of requisitions that often carry considerable uncertainty for a large enterprise. Throughout the study, the researchers worked with personnel from all procurement teams with their internal stakeholders at various stages.

Prior to the study, the procurement function already implemented a rudimentary short-term requisition planning process with varying degrees of maturity across the global business units. While some divisions still rely on ad-hoc spreadsheets, others utilize a tool-supported approach that is linked to the financial budget process and serves as the common database of requestors, requirement specialists, and controllers. There is a semi-automatic data exchange between the Pre-Planning Tool and the ERP system, which has a modularized structure, i.e., for requisition, order, and invoice process flows. In the figure below, the most relevant systems are summarized in an abstract form along with the respective time horizons, main users, and analysis scope. The information basis for bundling decisions in this study is shown with the center red frame while the traditional scope based on historical information is shown within the right frame. There is an additional opportunity for the case company to utilize the Pre-Planning Tool as another data source once a higher degree of maturity has been reached illustrated in the left frame.

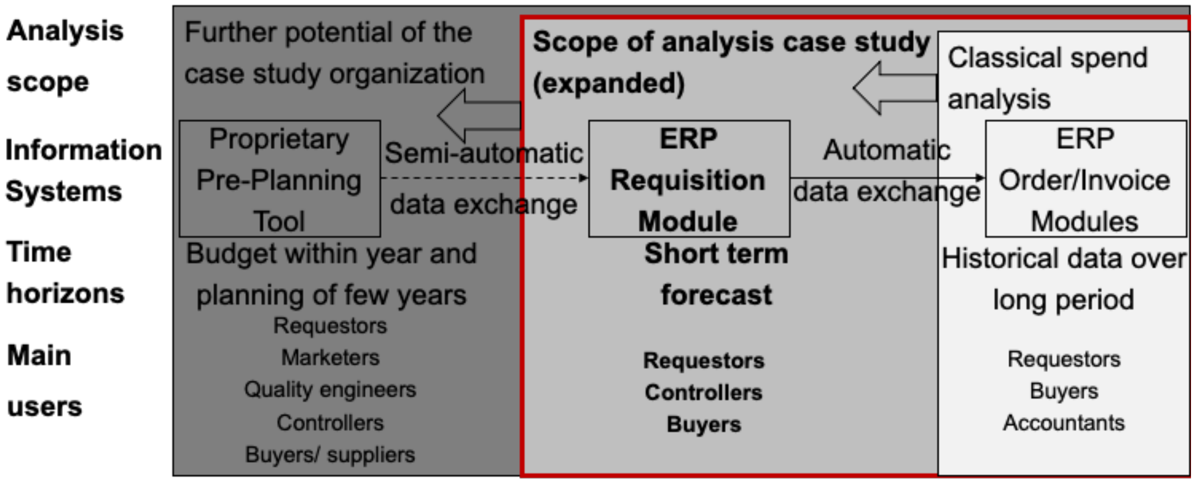

Figure 12: Case study scope, systems, horizons, and users

As illustrated above, several organizational roles are involved in the information flow and have a stake in bundling decisions. The information contained in the ERP Requisition Module is utilized in this work for creating bundling options although it is not as precise as information about already processed orders or invoices. The potential benefit of forward-looking data instead of spend analysis of the past is generally higher since not only data-driven decisions and what-if analysis may be based upon it, but it also can be used to devise commodity strategies and optimize tender designs instead of gaining insights, what could have been done better in the past. Thus, the units of analysis of this study are the clustered purchasing requisitions as recommendations to the buyers.

Procurement in larger public and private organizations typically involves several specialist teams that handle similar requisitions, internal business units, and external suppliers, while a smaller-scale enterprise may have only one employee managing all purchases (Monczka et al., 2020). However, as noted in Planergy (2022), each team in many organizations such as the focal company manually records upcoming requests for quotations. As often as not, there is no automatic data exchange, and communication can be slow and complicated across many stakeholders (Ma et al., 2018). Consequently, the bundling potential may not be readily apparent and only emerges during later sourcing process stages such as supplier selection committees, which may be too late to achieve significant cost savings.

The resulting cross-functional analyses likely lead to synchronization and adjustments of temporal and qualitative factors to make the bundled demands more accessible for the supply market and thus generate higher competition (Ozkul et al., 2012). As shown in Figure 12 above, the sourcing process is embedded in the budgetary planning as financial approval is procedurally required to purchase goods and services from the market. In the figure below, a general sourcing process in the focal organization has been created with buyers, controllers, accountants, requestors, requirement specialists, and quality engineers. It shows the tactical source-to-contract phase based on an established process model by Spina (2008) from the specification of the technical requirements to the request for quotation until finalizing the agreement, whereby the leading role is shown in blue and related activities in orange colorings.

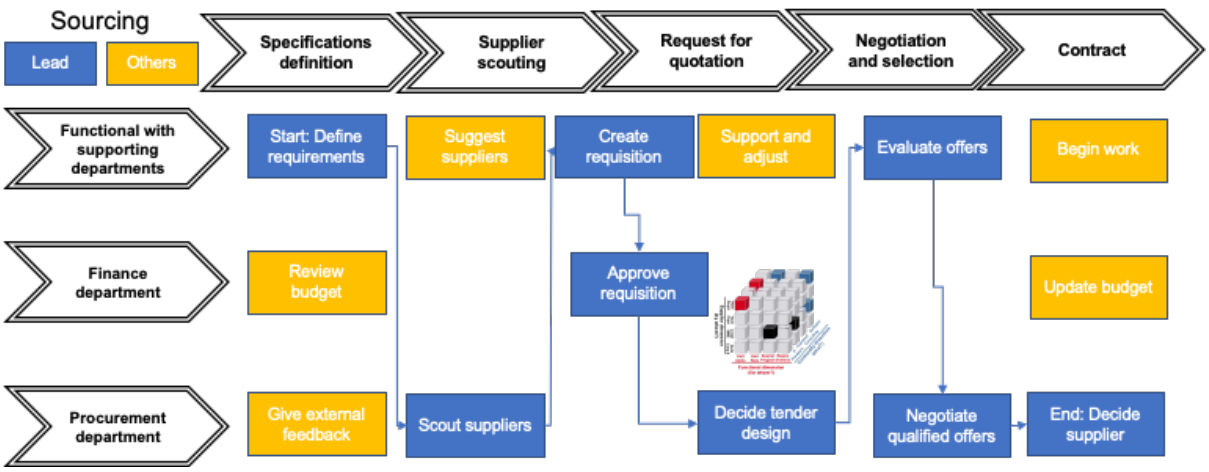

Figure 13: Artifact process embedded (own illustration based on Spina, 2008)

As illustrated above, the bundling generator serves as an important input for setting up requests for quotation also called tenders. Moreover, it generates data-driven insights on relevant requisitions that are currently in the creation or approval stages. A collaborative review of the technical requirements allows buyers to evaluate the viability of bundling options. The options can be ranked according to their savings potential. Operational feedback by the buyers after the initial setup can further improve the artifact, especially its confidence in the proposed clusters and approximation of savings, thereby refining the ranking mechanism. A manual alternative to a tool-based decision support solution is the spreadsheet analysis of the available information but does neither scale nor utilize the analytical performance improvement of human-AI collaboration in decision sciences. While principally the three dimensions of commodity, functional, and supplier are all relevant, in this study, an emphasis is laid upon product-centric component bundling due to data availability and the defined designed requirements described in Table 5 below.

Buyers are continuously identifying cross-department, cross-supplier, and cross-category saving potentials. No matter what support an information system can provide, these will likely continue to be core capabilities of professional buyers, whereby the bundling generator may augment their toolbox. Thus, the design artifact is purposefully not an autonomous system since the buyers as the main users should have a stake in how the tool works as suggested by Dietvorst et al. (2018) that may support them to gain unexpected insights - without presumed knowledge of what is feasible based on the dataset used to build the model. For the analysis and evaluation of the case study, requirements have been analyzed by the review of the literature and the information processing theory as outlined in the table below in a brainstorming session with the focal organization.

Table 5: Summary of design requirements for the artifact development

Requirements	Gathering	Processing	Communicating
Procurement management	Improve planning with stakeholders	Able to understand bundle creation	Receive feasible proposals with the possibility to provide feedback
Internal such as finance, marketing, and quality	Connect purchasing planning with financial planning	Ensure data protection and data privacy	Financial benefit with profoundly determined saving potentials

External in particular suppliers	No essential requirements identified	Ensure algorithm fairness	Receive tender invitations that fit the capabilities and capacities of the supply market

The two main factors of information asymmetry, uncertainty and equivocality, were considered in the analysis of the gathering, processing, and communicating stages as summarized above. While the explainability of the proposed bundles was important to the buyers, the most important requirement is that the action recommendations are feasible. This includes timing constraints since it is neither financially nor operationally advisable to expedite or delay necessary sourcings to a large degree. The time framework was discussed with the focal organization leading to a ninety-day timeframe for further model development, which proved robust in the sensitivity analysis. Generally, in interorganizational research, internal differences are often overlooked (Nitsche et al., 2021b). Therefore, in the research design, an emphasis was laid upon internal stakeholders of procurement for design requirement analysis.

While informal exchanges with solution providers of ERP and spend analysis were conducted during the setup and implementation of the study, based on the results summarized above, no design requirements of external stakeholders such as suppliers or governmental agencies have been identified. However, as indicated in Figure 12, feedback from the supply base about capabilities and capacities could provide valuable insights for strategic planning processes, as seen in the current semiconductor crisis that is severely impacting automotive and other major sectors (Schuh et al., 2022). Lastly, the artifact has been created in the programming language Python since it offers relevant standard packages, built-in functions, and support. To sum up, the bundling generator can be evaluated against these design requirements along with the subjective value assessment of the buyers as main users as well as the achieved cost savings.

3.2.3 Applied algorithms

Selecting the optimal model for generating the clustered bundles is a critical measure for ensuring the effectiveness of the generator. After data collection, exploration, and preprocessing in particular of the text information, different clustering algorithms that can group similar requisitions were created and evaluated in collaboration with the case study organization. Since no information about bundled future requisitions or labeled historical bundles was available, five supervised algorithmic models were trained as the core clustering engine of the bundling generator: K-means, Mini Batch K-means, Affinity Propagation, Mean Shift, and OPTICS.

These were selected based on the identified requirements for the artifact and the review of the literature in particular Schoenherr and Mabert (2006), Barraclough et al. (2012), and Li et al. (2015). They are described in this section along with the rationale, of why there were chosen. Other considered types of algorithms were, for instance, decision rule classifiers, regression models, decision trees, and support vector machines. Based on the available data, the main selection criteria for the algorithmic models were the ability to work with little and imprecise information without labeled data. As summarized in Table 5 in the previous section, for the buyers the explainability of the model was essential in order to understand and explain, how the proposed bundling recommendations have been created.

According to Haraty et al. (2015), K-means clustering is an iterative algorithm that partitions a dataset into distinct clusters where each data point belongs to only one group. The algorithm attempts to make the intra-cluster data points as similar as possible while keeping the clusters separate. The objective is to minimize the sum of squared distances between the cluster centroids and the data points, achieved by assigning data points to clusters (Wagstaff et al., 2001). K-means is frequently used as a baseline due to its ease of use, computational efficiency, and scalability to big data sets (Coates and Ng, 2012). However, this method has several limitations including its susceptibility to outliers, inadequate proficiency in dealing with clusters characterized by fluctuating sizes and densities, and difficulty in forecasting the ideal k-value.

Next, Mini Batch K-means is an algorithm that employs small fixed-size random batches of data that can be saved and retrieved in memory (Newling and Fleuret, 2016). According to Feizollah et al. (2014), the clustering process involves updating the clusters by utilizing a new random sample during each iteration until convergence. Additionally, the learning rate employed in each mini batch decreases with the number of iterations. With an increasing number of iterations, the impact of new data is diminished or weakened. Convergence is established when the clusters remain unchanged for a set number of consecutive iterations (Xiao et al., 2018).

Affinity Propagation is an exemplar-based clustering technique that utilizes similarities between data points to generate clusters (Frey and Dueck, 2007). The resulting set of exemplars assigns data points to the most appropriate exemplars. Wang et al. (2008) suggested several advantages, such as Affinity Propagation does not require a predetermined number of clusters, insensitivity to initialization, and the ability to find clusters with fewer errors than K-means.

Mean Shift is a popular mode-seeking clustering technique that detects the peaks in the data by maximizing the kernel density estimate (Carreira-Perpiñán, 2015). It is a non-parametric technique that can be applied to any dataset, enabling it to detect clusters of arbitrary shapes. Mean Shift does not require making any model assumptions, as the number of modes detected determines the number of clusters. Yuan et al. (2012) suggested that Mean Shift's computational cost in terms of needed resources and run time is expensive even on moderately large data sets.

Finally, OPTICS is a data clustering technique based on hierarchical density that removes noise and employs adjustable reachability thresholds to identify clusters of varying shapes and sizes (Khan et al., 2014). OPTICS does also not require a pre-specified number of clusters. It locates a set of high-density core samples and expands clusters from them, making the algorithm well-suited for large datasets with varying densities (Breunig et al., 2000).

3.3 Related literature

The utilization of data-driven strategies in business operations has resulted in significant changes to both buying and selling processes. Consequently, this shift has led to significant implications for operations and supply chain management (Sanders, 2016; Wamba et al., 2021). The bundling problem is one of the major challenges of buyers and marketers alike, of how to combine different requisitions and products into marketable bundles that are attractive to the other side (Schoenherr and Mabert, 2006), whereby AI-driven decision sciences can be essential to achieve higher value contributions (Gunasekaran et al., 2017; Li et al., 2023).

For the purpose of this study as in the following work in Chapter 4, the concept of artificial intelligence encompasses machine learning techniques, such as supervised learning and natural language processing, which are defined as a system's ability to effectively learn from data and employ those learnings to accomplish specific objectives by means of flexible adaptation (Russell and Norvig, 2020). In this section, the related literature is summarized on AI in procurement and B2B marketing, followed by a description of the bundling problem and spend analysis, and their decision support technologies in particular recommender systems.

3.3.1 Artificial intelligence in industrial marketing and procurement

As described in Spreitzenbarth et al. (2022a) comparing the technological adoption between purchasing with marketing and sales function, the utilization of AI in B2B marketing offers numerous possibilities to transform the tasks presently carried out by marketers (Syam and Sharma, 2018) similar to industrial buyers. Research such as by Nitsche et al. (2021a) and Cui et al. (2022a) has highlighted the potential of hybrid human-AI collaboration, however overall, artificial intelligence technologies are still under-investigated in operations and supply chain management (Sanders, 2016; Brinch, 2018; Nguyen et al., 2018; Brintrup, 2021; Li et al., 2023).

According to van Weele (2018), procurement, also known as purchasing or supply management, involves obtaining goods or services from an external source for requesting functions as their internal customer while striving to attain the optimal cost while fulfilling particular criteria in regard to quality, quantity, time, and location. This function must navigate competing goals, including constraints related to time, cost, and quality. External expenditures with suppliers typically account for more than fifty percent of the overall cost structure (Schuh et al., 2022). However, across all sectors of the economy, there is still an overall low usage of procurement analytics, whereby quality and data integrity issues are hindering performance increases (Gunasekaran et al., 2017; Handfield et al., 2019).

The procurement process is typically classified into two types: direct procurement and indirect procurement. Direct procurement concerns the acquisition of goods that are utilized in the production of final products such as tires, brakes, or batteries, whereas indirect procurement pertains to internal demands, such as logistics or engineering services (Monczka et al., 2020). Although cross-functional forecasting procedures are frequently implemented for direct procurement, obtaining high-quality data from stakeholders remains a challenge for indirect procurement (Planergy, 2022; Schuh et al., 2022). Requirement management and procurement planning are important parts of strategic category management (van Weele, 2018). Requirement management is an iterative process of exploration, documentation, and refinement of the essential deliverables over the lifecycle that can have substantial leverage to effectiveness and efficiency - and procurement requisition planning is the process of identifying and consolidating essential external demands with their time and quality constraints (Planergy, 2022). A requisition is an internal service order to the procurement function to purchase goods or services on behalf of the organization based on an allocated financial, temporal, and qualitative set of requirements. Thus, the bundling problem is intricately linked with the supplier selection problem, which is aimed to choose the supplier that offers the greatest value proposition (Monczka et al., 2020).

As pointed out in the literature review in the previous chapter, this aligns well with the idea of AI as a co-pilot for professional buyers that can augment their skills and expertise with AI-driven decision sciences. For instance, the Volkswagen Group has already integrated AI technologies into their operations to recommend alternative suppliers in indirect procurement and the German industrial corporation Siemens built a recommender system for prioritized activities to carry out and learns from the decisions by the team to suggest better actions in the future (Spreitzenbarth et al., 2022b). Also, Meyer and Henke (2023) developed ten general design principles for the application of artificial intelligence technologies in purchasing and supply management that have been drawn upon when evaluating the developed artifact to derive design principles for the bundling problem, spend analysis as well as requisition planning and requirement management in this study.

According to van Weele (2018), procurement can also be viewed as reverse marketing. Within the context of integrated supply chain processes that extend from the supplier's supplier to the customer's customer, procurement with sales and marketing serves as the primary boundary-spanning functions of an organization. Their inter- and intra-organizational challenges are linked, particularly through the demand planning process (Nitsche et al., 2021a). Additionally, bundling challenges exist for orders in production and service delivery functions (Ozkul et al., 2012). Due to the necessary focus, this study concentrates on bundling purchasing requisitions, compares and contrasts this to product bundling by their counterparts in industrial marketing and sales functions.

3.3.2 The bundling problem

To achieve better economies of scale, economists were first to analyze and propose optimal bundling policies (Adams and Yellen, 1976). The bundling problem is a business analytics topic that has been researched from various angles and decision parameters (Sarkis and Semple, 1999), for instance optimizing the purchasing of new and refurbished goods in health care (Ross and Jayaraman, 2009). The consistency of offers across the worldwide organization is facilitated by key account specialists on the seller side (Kotler and Armstrong, 2018). Lead buyers are analogous to key accounts within the buying organization (Monczka et al., 2020), wherefore the bundling generator could become a viable tool.

IBM developed a B2B recommender system that utilizes co-clustering principles to pair company clients with company products in order to identify potential client demands and cross-sales opportunities early (Vlachos et al., 2016). Although based on a different computational method, this study is the most similar approach described in the literature as it is generating prospective sales combinations, assessing their potential worth, and subsequently prioritizing them as leads for the sales team. Following its pilot implementation at IBM Germany, the system generated more than two hundred sales opportunities in one year, achieving a conversion rate of approximately ten percent (Vlachos et al., 2016). This study served as inspiration for the development of a similar tool in the purchasing domain.

In addition, marketing researchers have investigated the strategy of bundling items to improve offers to customers in terms of bundled pricing (Garfinkel et al., 2006). Bundling for consumer markets is thereby different from creating bundles in industrial markets or public institutions (Stremersch and Tellis, 2002). Grimm (2007) suggested four major factors that may influence a buyer's bundling decisions typically facilitated by commodity management: Synergies in operations, the degree of heterogeneity, the number of bidders, and cost uncertainty. Bundling can serve both as a method for purchasing machinery as a one-time event and for regularly procuring raw materials over varying time frames. The buyer can design the bundle structure and allow varying degrees of flexibility for suppliers to make offers based on this structure (Reyes-Moro and Rodríguez-Aguilar, 2004).

3.3.3 Decision support systems for bundling

Several studies have investigated the impact of procurement bundling on cost savings, i.e., Schoenherr and Mabert (2006) found that bundling can lead to over ten percent additional savings. Bundling typically reduces the number of suppliers, which allows buyers to focus on fewer external partners. Nevertheless, combining requisitions requires an initial effort to classify item groups that are appealing to suppliers and technically feasible in comparison to purchasing individual components (van Weele, 2018; Monczka et al., 2020). An additional challenge is that prospective providers may not possess the skills or capacities for all components, thereby requiring substantial investment or the outsourcing of certain components to a third party (Li et al., 2015). Despite these difficulties, Ozkul et al. (2012) suggest that suppliers are more likely to bid on unattractive opportunities when they are presented along with more desirable items.

Spend analysis is widely applied by practical decision-makers for understanding previous purchasing behavior and then generating projections for future spending (van Weele, 2018). It is an important input to the definition of procurement strategies to manage supply risks and optimize purchasing power (Sammalkorpi and Teppala, 2022). Thus, next to the internal requesting units and the external suppliers, spend analysis is often directed at the purchasing category, which requires an effective taxonomy such as ECLASS or the United Nations Standard Products and Services Code (Guida et al., 2023). Spend cubes can be generated by using data obtained from ERP systems or manual lists, which are projected as a multidimensional cube consisting of suppliers from whom purchases are made, functional areas for whom purchases are made, and categories of what is purchased as visualized in Figure 10.

Operational data is first extracted, transformed, and loaded into a data warehouse, whereupon online analytical processing can be carried out using a graphical representation to facilitate users. Artificial intelligence techniques can thereby strengthen data quality such as correctly classifying orders or aggregating spend from individual group companies to the holding structure (SAP, 2020; Sammalkorpi and Teppala, 2022). Material requirement management information systems are employed to effectively steer core manufacturing processes. However, as the focal organization is mainly concerned with product-related software and to better generalize the results of the study, data from the ERP system was utilized considering production and non-production requirements.

Technology providers like Amazon, Coupa, Jaggaer, SAP, and Sievo frequently employ recommender systems with collaborative filtering and content-based filtering techniques to assist buyers in locating pertinent information (Park et al., 2011; Spreitzenbarth et al., 2022b). While these systems have extensively been utilized in business-to-consumer settings, more research needs to be conducted in B2B contexts (Zhang et al., 2017). A key challenge is the scarcity of data, particularly for new customers with no prior business interactions (Zhang and Wang, 2005). This lack of data necessitates the use of indirect information that must be inferred.

3.4 Results and discussion

The results and discussion of the study are structured based on the three stages of information processing theory with gathering data describing the dataset and its preparation, followed by explicating the processing models, and finally communicating the findings to the community.

3.4.1 Gathering data

As illustrated in Figure 10, the recommendation engine takes as an input the requisition planning across the organization and outputs prioritized bundling options. Data from the ERP system as well as the project planning and budgeting Pre-Planning Tool were combined as well as stripped of personal and confidential information by the industry partner before handing the data to the researchers. In order to explore the data, the initial step was to collect relevant information and then proceed with a series of activities aimed at gaining a better understanding of the data. This involved carrying out a comprehensive description and analysis of the data, including its attributes, data types, and unique characteristics as suggested by Gregor and Hevner (2013).

The dataset consists of 751 shopping cart line items with mostly textual but also factorial and numerical information whereof three have been rejected by the buyer leading to 748 purchasing requests with over 20 attributes from April to August 2021 during the COVID pandemic and a volume of over 350 million euro across all spend categories, largely of indirect services. The majority of requisitions have been fully processed, yet 180 data entries are in different planning stages having lesser and more imprecise information. Feature reduction was applied due to missing or incorrect data entries based on initial model instantiations as well as the subjective assessment of the buyers. As a result, mainly information on the commodity dimension can be utilized. For instance, attributes containing information about suggested suppliers had to be dropped because of data quality. While explicit information on the requesting department was to a large degree removed due to confidentiality before the data was handed to the researchers, some insights about the functional department could be gained through the attributes of Cost Center and Internal Order. Nonetheless, the latter had to be discarded due to missing data entries, and the former did not show significance in the clustering models. This outcome was unexpected, yet no compelling explanation could be established.

One shopping cart may contain several line items that are processed together under a common identification number and are typically either budgetary or technically similar (Monczka et al., 2020). For consistency, all financial figures were rounded to the closed integer and converted into the currency euro based on the exchange rate set in source systems. It should be noted that for the model creation, only the manually labeled assessments by the buyers of the industry partner were available. Therefore, the dataset was not split into training and test sets, but the buyers' assessment of the bundles and the cluster characteristics were used for the evaluation. Selected examples of bundles by the Mini Batch K-means algorithm with respectively medium, low, and high expert assessment are shown in Table 13 in the Appendices, whereby the potential savings are exemplified for the ranking calculated based on Equation 4. Also, anonymous line items have been created and the attribute Product Description is not shown below to confidentiality.

While many practical reports and academic studies focus on direct procurement (van Weele, 2018; Monczka et al., 2020), as illustrated in Table 13 in the Appendices, the dataset includes a mix of direct and indirect procurement as the focal organization is mostly procuring services but also IT hardware and product-related software. To utilize the data directly by clustering algorithms for both the present study and future implementations in varying contexts, data preparation is necessary to train the clustering models within different organizational environments. While simple operations such as altering data types were sufficient for categorical and numeric values, significant preparation was required for textual data.

The first step in the analysis was to use a translator library (Yin, 2014) to convert textual information into English. Stop words were removed and the text was stemmed and transformed to lowercase. Word2Vec which is a widely used neural network that works without pre-existing labeled data und was utilized to generate embeddings for both the Product Description and ECLASS attributes (Gensim, 2022). Each word is thereby represented by a vector (Lilleberg et al., 2015), allowing mathematical operations to be performed on words to detect similarities. It was chosen over other techniques, such as fastText which operates at a more detailed level using character n-grams (Russell and Norvig, 2020) due to prior experience and accessibility.

In the figure below, the resulting bag of words was created in Python at the example of Mini Batch K-means to visualize the data processing of the free text Product Description.

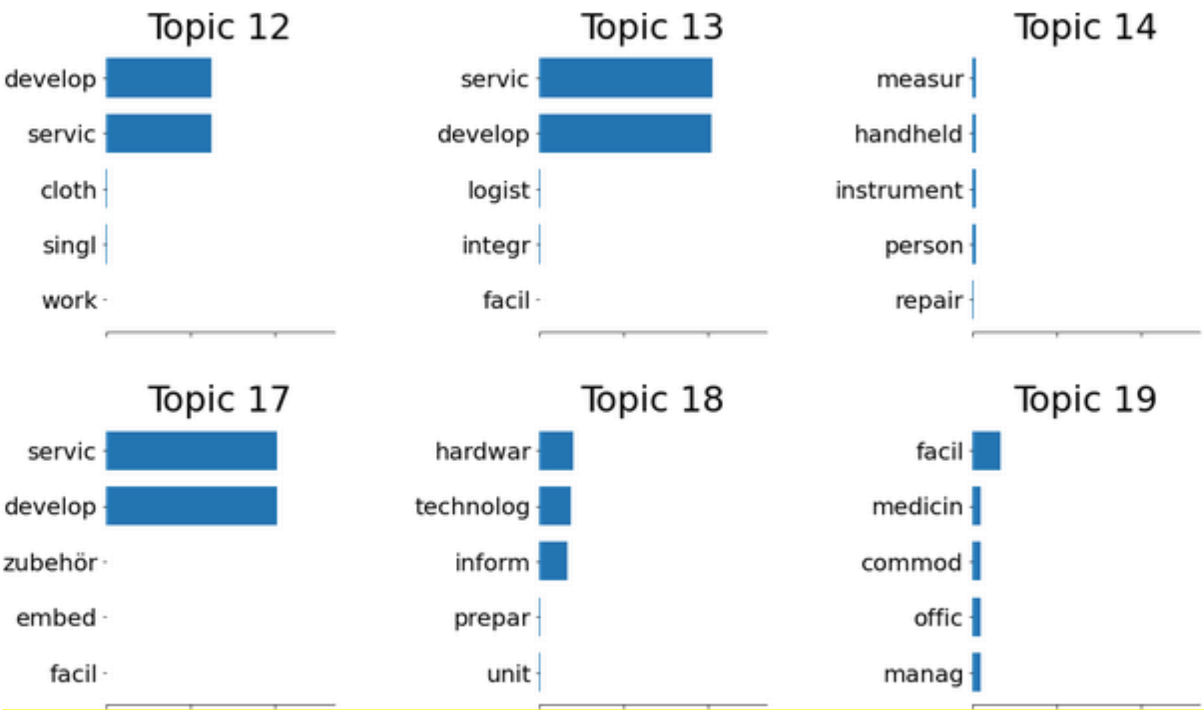

Figure 14: Bag of words Mini Batch K-means example (with permission Farida, 2022)

Document vectors were created using the Word2Vec model with a vector size of 100. Since this model produces numerical vectors for every word within a document, it was essential to derive a singular vector from them. To address this, the average of vectors was utilized due to the relatively short text found in the attributes Product Description and ECLASS, which is a four-tiered classification standard that is used across all categories and industries (ECLASS e.V. Association, 2022). The ECLASS attribute was effective next to Product Description when creating the algorithmic models since the classification is well maintained in the case study organization and contains aggregated information through its hierarchical numbering system.

3.4.2 Processing models

The five selected algorithms summarized in Table 6 below were implemented and iteratively improved in exchange with the buyers. First, following Bholowalia and Kumar (2014), the value of k or the number of clusters for K-means and Mini Batch K-means was established by the elbow method. This approach involves plotting the values of cost against different values of k. The curve representing the average value of cost declines as the number of clusters increases because of the reduction in the number of elements per cluster, which brings the elements closer to their respective centroids. The elbow point where the curve experiences the steepest decline, is the optimal number of clusters resulting in the creation of 110 clusters for both algorithms.

The Affinity Propagation model was fitted using a damping factor of 0.94, indicating the degree to which the current value is sustained in comparison to the incoming values, while the default values provided by the widely used Python package Scikit-learn (2022) were used for the other parameters. For Mean Shift, the bandwidth attribute was chosen as the input, and the value of the bandwidth was determined using the estimate-bandwidth function from Scikit-learn with default parameters, except for setting the quantile parameter to 0.5, which applied the median of all pairwise distances. However, the distribution of the bundles is disadvantageous for bundling purposes with one large incoherent cluster and many small clusters. Finally, the clusters by OPTICS were similar to Mean Shift but slightly more uniform and consistent.

Among the five algorithms, Mini Batch K-means exhibited the highest performance in terms of generating uniformly and consistently good options, while Mean Shift demonstrated the poorest performance. In the table below, the total number of bundles as well as the largest bundle and smallest bundle for each algorithm is summarized. Generally, larger clusters are relevant for bundling if they are well-composed. The smallest possible cluster has the size of one, which means that the models did not find sufficient similarities between the requisitions. The largest bundle was a 350-item bundle created by Mean Shift, which also led to many one-item clusters. In contrast, the largest cluster of the Mini Batch K-means algorithm includes 28 line items. In addition, this instantiation of the bundling generator created only five one-item groups and relatively uniformly sized bundles. As shown in the table below, the largest saving potential is similar across all models due to a high-volume requisition in the dataset.

Table 6: Proposed bundling opportunities by the applied algorithmic models

Bundle characteristics	Largest bundle	Smallest bundle	One-item bundles	Total number	Largest saving
K-means	56	1	20	120	5,663,776
Mini Batch K-means	28	1	5	110	5,553,260
Affinity Propagation	28	1	89	180	5,271,858
Mean Shift	350	1	55	120	5,259,118
OPTICS	124	1	26	120	8,419,191

For the assessment of the proposed clusters, they were first assigned to two buyers according to their expertise and judged individually in terms of low, medium, and high confidence. If the confidence assessment did not concur, the buyers collectively reviewed the bundles. When needed, they collaborated with the requestor and stakeholders as needed to reconcile. The buyers reported that some of the clusters were surprising to them in the sense that the bundles are across different pathways of what is normally analyzed within the organization. In addition, the buyers described that temporal factors such as project time pressure and conflicting schedules can make it difficult to bundle demands across the organization. This is reflected in the model’s learning as, for instance, the attribute SC Creation's dates were found to be the second most influential factor in determining the clusters of Mini Batch K-means.

Finally, the value of the shopping carts in each cluster is considered together with the model confidence normed by dividing it by two for low confidence denoted as 1, medium denoted as 2, and high denoted as 3 to deprioritize negatively assessed clusters. The algorithms with their proposed clusters have been ranked according to their potential savings with the following equation based on the conservative assumption as outlined in the methodology that two percent cost savings can be achieved for all models and items i in the proposed clusters.

Equation 4: Calculating the potential savings

$$\forall \; clusters \; t \; and \; items \; i\text{:} \sum_{i=1}^{j} \frac{confidence \; i}{2} * \frac{2 * shopping \; card \; value \; i}{100}$$

The average savings of the clusters proposed for example by Mini Batch K-means is €97,423 with several bundling opportunities of over one million euro ranging widely from €8 to €5,553,260. Their distribution is left-skewered with many low-value bundles and some large savings opportunities that can be prioritized and cross-functionally perused. Another reason why Mini Batch K-means was so well received by the buyers was that the proposed bundles were not only well clustered but as summarized in Table 6 also not too large and not too small, and thus hold meaningful savings potentials but are still operationally feasible to bundle with acceptable effort. To conclude, the Mini Batch K-means performed the best among the five selected clustering algorithms based on the expert assessment by the buyers of the case study organization, where the proposed clustered bundles were most highly evaluated. In addition, the identified bundling opportunities were comparatively uniformly distributed with few one-item clusters and no very large clusters that would be difficult to effectively combine in practice.

3.4.3 Communicating results

As outlined in the methodological section, to empirically identify saving potentials by bundling, data can be merged, e.g., from information systems for sourcing, enterprise resource planning, and manual planning tools along with the three dimensions of commodity, functional, and supplier. Overall, it was surprising to the buyers that the AI-based models were able to detect similarities mainly based on the attributes Product Description, ECLASS, and time stamps. This showcases that the employed supervised algorithms could cope well given appropriate data preparation considering the size of the dataset with a fairly high degree of missing entries and incomplete information about the requisitions. In addition, in Figure 14, a bag of words has been created in Python for the Mini Batch K-means algorithm to visualize the preprocessing and processing of the free text Product Description.

The achieved savings are not disclosed in exact figures; however, the results overall confirm the findings of Schoenherr and Mabert (2006), whereby cost savings range between one and twenty percent through improvements in tender design and negotiation due to the volume increase and higher competition. Furthermore, the bundling generator led to more difficult-to-measure advances in operating process costs, supply base optimization, and cross-team communication as well as the general perception among the involved personnel in the case study organization of purchasing as a “cool and savvy business function”.

During the discussions with the involved stakeholders in the focal organization, it was evident that they were surprised by the model’s accuracy in terms of finding meaningful similarities in the requisition data. Thereby, the bundling generator illustrated the value of the procurement planning data and motivates a common discussion early on to actively involve procurement in financial budgetary decisions and also functional requirement evaluations that typically define the total cost of ownership in an early stage of the product development cycle (Monczka et al., 2020). Once a higher degree of maturity and consistency of the general financial planning has been reached, which is ideally connected with the overarching demand management and strategic procurement planning across all business units, the bundling decision analysis could be based upon a mix of historical and future-looking information that may lead to the identifying of more cost savings opportunities.

Several buyers and stakeholders provided overall positive feedback as well as suggestions summarized subsequently in this section to further improve the design artifact. The ranking of the bundling opportunities based on the potential savings calculation was found useful as well as the possibility to provide feedback and thereby be actively involved in the model development. This fits with the finding of Dietvorst et al. (2018) that human agents generally like to work with a model if they are enabled to provide feedback that will modify them. Thus, the utilization of the bundling generator can significantly enhance the predictability and clarity of bundling possibilities, thereby rendering their cost-saving advantages more concrete and measurable. This helps to address the rising demand for information and information asymmetry by creating structural mechanisms that facilitate the flow of cross-functional information (Galbraith, 2014). As illustrated in Figure 11, the bundling generator quickly became an important input for setting up requests for quotation. The artifact can thereby be used to generate data-driven insights on upcoming requisitions that are currently in creation or approval and thus earlier than after the final approval of the shopping cart.

Discussing the results with technological solution providers, the most interest was in combining historical spend data with forward-looking requisition data. In contrast to the buyers and internal stakeholders of the focal company, they were not surprised by the effectiveness of the artifact based on such mere information but were especially interested in the collected design requirements summarized in Table 5 and the deduced design principles in the table below, especially how the artifact has been embedded in the case organization as illustrated in Figure 12 in terms of the connection of the financial and procurement planning process.

Considering the information-processing needs of the functional departments, finance, legal, marketing, quality, procurement, and suppliers in private and public settings, generalized principles have been derived for solutions providers and purchasing organizations. Thereby, the compiled stakeholders' expectations during the earlier stages of the design science process were utilized as the basis of discussion. Again, the two factors of information asymmetry, uncertainty and equivocality were considered together in the gathering, processing, and communicating process stages. The design principles summarized in the table below have been initially created in a brainstorming session with the focal organization based on the results of the case study as well as the discussion of the related literature such as Meyer and Henke (2023) and have iteratively improved as outlined in the design science approach in Figure 11.

Table 7: Deducing design principles from the developed artifact

Design principles	Gathering	Processing	Communicating
Bundling problem	Move from ad-hoc manual to regular value-driven data collection	Automatic processing to identify and rank potential bundles	Ensure transparency with the ability to provide feedback
Spend analysis	Able to integrate with relevant information systems through programmable interfaces	Enable forward-looking analysis based on more uncertain planning data	Visualize bundling scenarios to buyers and stakeholders, how the budget could be spent
Requisition planning and requirement management	Utilize information from functional, budgetary, and purchasing planning	Automatic processing connected with relevant systems	Strengthen and align cross-functional exchange through a common decision basis

During the evaluation of the developed artifact, no specific risks posed by the bundling generator have been identified other than the indirect effect that consolidation of requirements typically leads to a smaller supply base (Ozkul et al., 2012). In most instances, the advantages of a condensed supply base outweigh the drawbacks, however, it must be carefully managed by the procurement organization (van Weele, 2018). Yet, developing and maintaining a proprietary tool can be costly. Thus, ideally, the bundling generator would be an integrable module within a coherent analytical framework in the information systems landscape that may be part of the pathway toward the vision of procurement 4.0. This is pertinent for solution providers of spend analysis as well as ERP systems that could integrate such a bundling algorithmic model in requisition modules to provide a better decision basis for setting up requests for quotation and preparing negotiations across all their clients and can utilize other internal and external data sources by standard implementations rather than building up separate one-purpose tools. For instance, when analyzing to-be-bought requisitions, similar past purchases could be highlighted to the buyer with information about prices and conditions as well as current suppliers.

While case studies and frameworks such as design principles do not constitute theory, they can be a vital part of the theorizing process leading to new theoretical insights (Eisenhardt, 1989; Gregor and Hevner, 2013). Generalizing from a case study of a large organization in automotive as a capital-intensive industry with a high degree of external expenditure may be applicable since it is profoundly impacted by digital technologies (Dremel et al., 2017). The results especially the collected requirements in Table 5 and the derived design principles summarized in Table 7 may be applicable to tool providers and procurement organizations. In addition, the developed solution to the bundling problem with the aforementioned design requirements and design principles may be transferable to other disciplines such as production, logistics, or marketing. Furthermore, although each organization has its unique characteristics and thus captures data individually that is used by differently trained people working on the bundling problem, the fundamental challenges faced by buyers are similar, especially in capital-intensive settings and complex organizations with a large degree of external expenditures that still often face the difficulty having to make intra- and interorganizational decisions with uncertain and imprecise data.

As possible next steps, the bundling generator can be kept as a stand-alone tool to support the case company with identifying and prioritizing bundling opportunities continuously learning from feedback by the buyers as well as more training and test data. In addition, as the focal organization matures, the review of the proposed options can be used on an ad-hoc basis but ideally will be integrated into strategic procurement planning in collaboration with technical, marketing, and finance stakeholders based upon a commonly used database in a structured monthly or quarterly process as visualized in Figure 12. Other instantiations of the bundling generator can be created within or outside the group that would enable a cross-case analysis to further strengthen the generalizability and refine the design principles summarized in Table 7.

There are further supervised clustering algorithms that could be evaluated in future research. Also, unsupervised learning could further enhance the proposed cluster of the bundling generator incorporating the labeled data gathered from expert buyers in this case study. Another way for improving the recommendations of the bundling generator could be utilizing artificial intelligence techniques to increase the data quality of the input data. In this context, this could be particularly useful for the attribute ECLASS since although it has shown effective in the model development, the taxonomy is still fairly complex so that in practice especially requisitions are often misclassified by functional requestors and are then manually correctly when creating purchasing orders based upon the approval requisitions although most organizations already utilized a reduced ECLASS tree (Guida et al., 2023). For instance, hierarchical clustering algorithms can create an adjusted ECLASS estimator based on the other attributes of the dataset for each requisition before the data is fed into the bundling generator.

Lastly, the profound technical discussion of bundling options from cross-functional perspectives has often led to a better understanding of own preferences, which is essential for successful negotiations of all involved parties. The artifact thus facilitated communication and collaboration between different procurement teams as well as cross-functionally with the stakeholders as it made potential savings transparent.

3.5 Conclusion

The study empirically contributes to the literature and practice of the bundling problem with a case study of a global automotive original manufacturing group across direct and indirect procurement teams. It adds to the literature on design science research and information processing theory in procurement and supply management, decision sciences and recommender systems in the business-to-business area, and artificial intelligence in operations and supply chain management. Based on the design science methodology, a practical useful artifact has been created to deduct design principles for tool providers and procurement organizations in manufacturing and service contexts as visualized in Figure 11.

3.5.1 Theoretical contributions

While demand forecasting is commonly used across the organization, this is the first known study on the bundling problem and generally spend analysis to integrate historical data with forward-looking requisition data having inherently lower levels of information richness and precision than past purchases. Furthermore, a novel approach to provide analytical decision support for bundling is offered augmenting the skills of buyers to identify cost saving potentials. The study contributes to information processing theory and the design science methodology, which is still underrepresented in operations and supply chain management.

Overall, Mini Batch K-means was the most performative model among the five selected clustering algorithms based on the expert assessment by the buyers of the focal organization. In addition, the proposed bundles were uniformly distributed with few one-item clusters and no very large clusters as summarized in Table 6. As the practitioners reported, the recommended bundles are therefore not too large and not too small, and thus hold meaningful savings potentials but are still operationally feasible to bundle with acceptable effort. The results may be transferable to bundling problems in neighboring areas in particular production and logistics, service management, and industrial marketing. The work is thus contributing to how AI-driven decision sciences can increase operational performance, especially to the current discussion of automation versus augmentation of AI in management research initiated by Raisch and Krakowski (2021).

3.5.2 Practical implications

The created artifact has implications beyond the context of the case company but generally for public and private purchasing teams, particularly in complex organizations and industries with a high degree of external expenditure - as well as for tool providers that may extend analytical frameworks with forward-looking requisition data, whereby the collaborative evaluation led to generalized design principles summarized in Table 7. The buyers and stakeholders highlighted that while some technically and financially sound bundles were not feasible in practice due to not directly changeable temporal and capacity factors, the ranking of the bundling opportunities based on the calculation of the potential savings in Equation 4 was found beneficial as well as the possibility to provide feedback and thus actively be involved in the model development.

The achieved cost savings cannot be disclosed in exact figures; however, the results overall confirm the findings of Schoenherr and Mabert (2006), whereby substantial cost reductions could be achieved by improvements in tender design and negotiation power due to the volume increase and higher competition. In addition, the bundling generator led to more difficult-to-measure advances in operating process costs, supply base optimization, and cross-team communication as well as the general perception among the involved personnel of purchasing as a “cool and savvy business function”. In general, the results show that based on a comparatively small data set with mainly a free text description, the ECLASS taxonomy, and time stamps, the recommender system could provide a solid decision basis for bundling purchasing requisitions.

While building performative algorithms based on so-called little data used to be a major limitation of artificial intelligence in the past, literature as well as this empirical research indicates that this assertion may no longer hold. This finding is promising for the field of operations and supply chain management which often must work with little information to solve relevant problems. For instance, enterprise resource planning systems could integrate such a bundling analytics model in requisition modules to provide a better decision basis for setting up requests for quotation and preparation of negotiations across all clients. In addition, the bundling generator could be part of a larger AI module adjunct to the tendering system, i.e., to propose bidders for a project leading to further process efficiencies. The study thereby contributes to advancing the field of business analytics through developing empirical methodologies in novel ways in order to solve the bundling problem as a significant business intra- and interorganizational decision-making problem by introducing an innovative, generalizable approach with state-of-the-art analytical techniques, i.e., supervised learning and natural language processing with real data.

The artifact can support strategic commodity management through AI-driven decision support. As described in the review of the literature, while direct procurement, often already employs cross-functional forecasting procedures, indirect procurement typically faces challenges in obtaining high-quality data with their stakeholders. The bundling generator may contribute to addressing this issue and provide a tangible reason to commonly focus on requirement management and share information on future external demands, as the value of such collaboration can be demonstrated to functional departments as the internal customer of procurement in terms of cost savings and improved planning security, e.g., by setting up long-term framework contracts with key suppliers.

In addition, the decision support system assists expert buyers in gaining unexpected insights based on the data without presumed knowledge of what is feasible. The buyers reported that some of the proposed clusters were surprising in the sense that they propose bundles across different pathways of what is normally analyzed within the organization and therefore highly useful. Thus, the bundling generator can support their role within the organization and may contribute to the data-driven transformation toward procurement 4.0.

3.5.3 Limitations and future research

While the five clustering algorithms were collaboratively selected based on the in-depth review of the literature and the identified requirements summarized in Table 5, there are further supervised algorithms that could be evaluated in future research. Unsupervised learning algorithms may further enhance the proposed cluster by incorporating the labeled data gathered from the expert buyers in this study, Also, as exemplified by IBM's business-to-business recommendation engine for key account managers in Vlachos et al. (2016), a textual explication of the rationale behind the clustering process might amplify the accountability of the results.

Moreover, as the artifact is utilized, not only can more historical and planning information be used but also the functional data input quality might increase, whereby especially the supplier dimension could enhance the bundling generator. In addition, while the Word2Vec neural network proved useful to preprocess the textual data to be used by the clustering models, fastText is an alternative approach to text representation that may refine the action recommendations to the buyers and thus lead to better decisions and more cost savings for the organization. Another way for improving the recommendations of the artifact could be artificial intelligence techniques to enhance the data quality of the input data, e.g., hierarchical clustering algorithms can generate an adjusted ECLASS estimator based on the other attributes of the dataset for each requisition before the data is fed in the bundling generator.

The data collection and objectives of the study are inadvertently biased in what data is available, which questions are asked, and what goals are important. Thus, the data used to develop the models contains these inherent biases as well as what types of requisitions are needed and how they are classified. As the data is from 2021 during the COVID pandemic, they are tilted toward essential goods and services. Yet, when data is continuously collected to further optimize the generator, this will not structurally influence the action recommendations in the future. Furthermore, the developed models can be applied in different organizational environments leading to a multiple case study research design comparing the results in terms of accuracy, hard and soft performance measurements such as cost savings and internal perception as well as the effort for data exploration, model fine-tuning, and process adjustments.

Lastly, while informal exchanges with established and emerging tool providers were useful for the setup and implementation of the case study, formal interviews, i.e., by semi-structured protocol could provide further insights. In addition, as visualized in Figure 12, information from the supply base about capabilities and capacities may provide essential insights for the long-term organizational planning that is evident in the recent semiconductor crisis severely impacting automotive and other major industries. To sum up, the results of the case study are encouraging for further research and applications of the bundling problem that holds significant leverage to core purchasing and supply management objectives, whereby the bundling generator can serve to augment the skills of buyers, especially in large public and private organizations worldwide.

Chapter 4 Ethics for autonomous agents in business negotiations

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Negotiations are an essential part of business and everyday life - and can benefit all involved parties to better approximate Pareto-efficient agreements. The study examines the ethical implications of utilizing autonomous agents in the context of business-to-business negotiations. This pertains particularly to how autonomous agents affect the power dynamics between buyers and suppliers. An ethical design framework has been iteratively derived based on the related literature and a thought experiment following the structured design science iterative methodology that may guide the further development and application of these emerging information systems. The study draws from agency theory and the literature on artificial intelligence in industrial marketing and procurement, ethics for artificial intelligence, outsourcing, contract law, and autonomous agent research.

In addition, the thought experiment examines, which questions five major normative ethical schools of thought might consider, what they may see as the main ethical implications, and how to address them when autonomous agents negotiate with other autonomous agents, humans, or hybrid human-AI teams. The work contributes to literature and practice in three ways. Firstly, to the design science methodology and ethics for artificial intelligence; secondly to principal-agent theory by linking the investigation of autonomous agents with established outsourcing literature; and thirdly to the development and operation of autonomous agents in business negotiations.

4.1 Introduction

This work examines the ethical implications of utilizing autonomous agents based on artificial intelligence in the context of business-to-business negotiations at the purchasing-marketing interface with a focus on the buyer's perspective. Artificial intelligence systems are becoming more and more autonomous, apparently smart and rational. As pointed out in the introduction of this dissertation, since in many industries typically more than fifty percent of the value is generated by suppliers, business negotiations have a significant impact on the overall success of the organization (Vollmer et al., 2018; Schuh et al., 2022). However, in a recent literature review of artificial intelligence in procurement described in Chapter 2, no study was identified focusing on ethical considerations of these emerging technologies, whereby for the use case autonomous negotiation there was a stark divergence in the assessments of the expert interviews, i.e., some experts questioned the value for autonomous negotiations while others highlighted the efficiency improvements for small requisitions and also the potential to combine the strengths of human and AI-based negotiators (Spreitzenbarth et al., 2022b).

One common AI design approach is to automatically learn by observing human behavior. The social network Facebook has used this approach to train artificial negotiators with the unintended consequence that they learned to lie (Gratch, 2021). In addition, the language models started to negotiate in their own language which has been compared by the involved researchers like the way humans create abbreviations: "*I can i i everything else*" (AI Business, 2017). This project was thus halted, but in late 2022, the research laboratory OpenAI trained a new generative pre-trained transformer language model called ChatGPT that has gained much interest but also continued criticism of inherent biases (Alba, 2022) similar to Google where a software engineer believed that the AI became sentient (Tiku, 2022).

The objective of negotiation is typically understood as finding improvements by exploring common grounds but also critical differences, whereby Pareto-efficiency describes a situation where no party can improve without adversely affecting any other (Jennings et al., 2001). There are emerging start-ups such as Pactum in the United States of America or Botfriends in Germany as well as existing technology providers such as IBM that are working to build often chatbot-based autonomous negotiation tools for industrial buyers and marketers (Spreitzenbarth et al., 2022b). Chatbots are dialogue systems that allow users to communicate with the bot in natural language via text input and buttons (Botfriends, 2022). These bots can be used to automate or augment different phases of the sourcing process including the negotiation stage, and also other key operations and supply chain management processes such as capacity management (Booth and Sharma, 2019). As the technology will become more readily available, ethical considerations for autonomous agents especially at the purchasing-marketing interface are increasingly essential for their acceptance and generally buyer-supplier relationships (Papa et al., 2019; Nitsche et al., 2021a) leading to the research question: **What are the major ethical implications of autonomous negotiation agents at the buyer-supplier interface and how could they be addressed?**

This is significant since leveraging AI could become a significant power factor in the future, especially in the interaction with external partners. In addition, autonomous negotiation agents may be part of the data-driven transformation of procurement and B2B marketing toward industry 4.0. Ethical implications in procurement are manifold and recently received increased attention, for instance due to regulatory requirements such as the recent Supply Chain Act in Germany (The Federal Government, 2022). While other studies focus on the role of the designers in creating autonomous agents such as de Vreede et al. (2021), this work concentrates on ethics by design searching for design principles as normative statements on how these negotiation agents should be programmed to interact with external partners. Accordingly, the term agent is seen in view of the principal-agent theory focusing on their behavior and relationship with internal and external entities rather than general principles of moral agents or more generally what inherently differentiates human and autonomous agents. Thereby, this paper aims to take part in the current discussion of automation versus augmentation in management research (Raisch and Krakowski, 2021), firstly by theorizing when and how to deploy autonomous agents in business negotiations and secondly by initiating an academic conversation over ethics for autonomous negotiation agents - in addition, the study contributes to answering the overall research question of this dissertation by examining an essential but also controversially discussed use case of artificial intelligence in procurement.

The remainder of this article includes the research methodology and a review of the literature. This is followed by a thought experiment of what questions five normative traditions may ask when considering the ethical implications of autonomous negotiators. Afterward, the literature and thought experiment are merged into an ethical design framework following the design science approach, and the results are discussed. Finally, conclusions are drawn, and the limitations of the study are laid out along with directions for future research.

4.2 Material and methods

The design science approach describes an iterative process that links existing knowledge with the practical environment (Torno et al., 2022). As pointed out in the previous chapter, design science research in purchasing and supply management is still underrepresented but has recently gained momentum (Srai and Lorentz, 2019; Stange et al., 2022). For instance, Meyer and Henke (2023) developed ten general design principles for the application of artificial intelligence technologies in procurement that have been drawn upon to derive the design principles for autonomous negotiation agents in this study. Based on the discussion of the related literature and the thought experiment, meta requirements and design principles have been derived as illustrated in the figure below similar to Figure 11 summarizing the design science process of the bundling generator in the previous chapter. The design cycle represents the core of the structured research process and is used to develop and evaluate the ethical framework as the focal artifact.

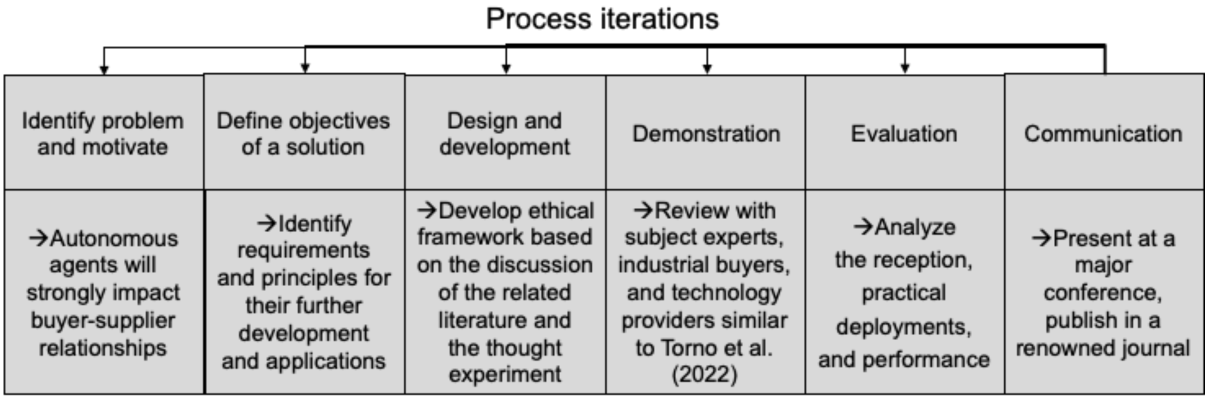

Figure 15: Iterative design process (own illustration based on Peffers et al., 2007)

The first step consists of the problem formulation whereby the relevance of ethical autonomous agents in business negotiations is investigated. In the second and third steps, requirements from scientific knowledge and standards are used to improve these to form a coherent framework. A thought experiment is carried out, on how five main schools of thought, namely pragmatic, utilitarian, virtue, role, and deontological may think about the issue in order to consider the consequentialist research question of this work from diverse ethical standpoints, of what are the major ethical implications of autonomous negotiation agents at the buyer-supplier interface and how could they be addressed. Thought experiments are methodologically a widely used type of experiment especially in applied ethics literature (Brendel, 2004), however, they have seldom been applied in operations and supply management (Spina et al., 2016; Tate et al, 2022). Generally, thought experiments can reveal transformation knowledge since such experiments question the current view of the world. Thus, they are not only normative in their design but also in terms of the possible results (Walsh, 2011).

Further considered normative ethical perspectives were in particular Islamic philosophy and southern African relational and communitarian ethics perspectives, however, the ethics in AI literature (Wilburn, 2022; Gordon and Nyholm, 2023) and thus knowledge on these were not sufficient to be examined in appropriate detail in the thought experiment. Following Walsh (2011) necessary details and justifications must be well described, i.e., what is the purpose of the experiment as well as what perspectives are considered and for which reason. These five traditions were chosen after the review of the literature on buyer-supplier relationships, principals and agents in business negotiations, and ethics in AI where often utilitarian, virtue, and deontological normative ethics approaches are put forward that typically lead to starkly contrasting analyses. In addition, non-traditional perspectives in particular pragmatic and role schools of thought have been selected that are currently underrepresented in research and practical reports (Bench-Capon, 2020; Wilburn, 2022).

Overall, many relevant questions for autonomous negotiation agents have not been yet addressed in the literature highlighting the need for this study and further research (Baarslag et al., 2017; Mell et al., 2020; Gratch, 2021). Finally, through an iterative process of demonstration, evaluation, and communication with negotiation specialists, technical experts, and ethical philosophers, the deontological design framework can be continuously improved. Other scholars can build upon this work for similar frameworks in industrial marketing, procurement, or adjunct disciplines and employed in practice by purchasing and marketing organizations as well as technology providers as outlined in the design science approach in the figure above.

4.3 Related literature

In this section, the related literature on buyer-supplier relationships, principals and agents in business negotiations, and ethics for artificial intelligence is reviewed and summarized.

4.3.1 Buyer-supplier relationships

Buyer-supplier relationships have been studied in different contexts, for instance of Japanese automotive original equipment manufacturer Toyota in Langfield-Smith and Greenwood

(1998). There are several crucial factors to consider that might be relevant for the introduction of autonomous negotiation agents. These include the similarities between the industries and the core technologies of the buyer and suppliers, the suppliers' past experiences with change, effective communication between the buyer and suppliers, and the significance of experiential learning in accepting change.

Traditionally, buyers had to choose where to focus attention to improve outcomes on multiple dimensions with time, budget, and quality factors, which resulted that many low-value requisitions are merely, if at all negotiated (SAP, 2020; Botfriends, 2022). Technological tools such as catalog management systems like Amazon Business or GEP Smart for spot buying have been developed to ease this issue (Lindsey, 2020; Spreitzenbarth et al., 2022b). In addition, negotiation support systems are utilized for the preparation of strategic negotiations as well as electronic auction platforms that are typically adjacent to the tendering system and can be seen as a precursor to an autonomous solution (Rogers and Fells, 2017).

As Saini (2010) pointed out that while considerable research attention has been given to ethics in marketing and sales, ethical issues for the procurement function deserve further research attention to holistically consider relevant questions of buyer-supplier relationships. Generally, the ethical lens has been largely underrepresented in operations and supply chain management (Quarshie et al., 2016). In examining how ethical industrial buyers are behaving in practice, Browning and Zabriskie (1983) defined ethical behavior as the "*use of recognized social principles involving justice and fairness in situations that are part of business relationships*" (p. 219). As pointed out by Chen (2023), most studies on procurement ethics have been conducted years ago and there is a need to conduct further research given the recent developments in digitalization and sustainability. For instance, in the 1980s and 1990s, several studies explored ethical issues associated with purchasing activities and identified potential unethical behavior of human buyers (Cooper et al., 2000). In contrast, autonomous agents may be unbiased and could be free of unethical behavior, if designed and trained well. For instance, a bot as a negotiation agent for a public or private organization does not receive gifts or free entertainment that could influence a supplier selection decision.

Previous research has shown that some procurement managers take pride in being deceitful to suppliers (Hill et al., 2009). However, unethical procurement practices may have substantial financial consequences and could induce serious reputational damage (Bendixen and Abratt, 2007). In addition, buyer-supplier relationships can be damaged or even terminated when suppliers feel that they are not treated fairly (Liu et al., 2012). Information about the unethical behavior of a buying organization may also reach potential suppliers of the buying organization, possibly causing the buying firm to lose some power over its suppliers. In addition, anecdotal evidence suggests that unethical and even unlawful procurement practices still occur, with a significant impact on both individuals and organizations. For instance, in April 2022, a former manager of Coca-Cola Enterprises was charged with taking more than one million pounds in bribes in exchange for awarding contracts to favored suppliers (Croft, 2022). The same month, the defense consortium Airbus pleaded guilty to corruption for paying bribes to high-raking Saudi Arabian military officials (Beioley, 2022).

Generally, human negotiators often develop a preferred set of negotiation styles. When negotiators utilize hard-bargaining tactics, they convey that they generally view negotiation as a win-lose exercise (Mell et al., 2020). Yet, only a small percentage of business negotiations concern just one issue, such as price, and thus can be viewed as win-lose negotiations. The management consultancy BCG described an AI-based coach to support negotiations estimating that an additional savings of five percent may be feasible if negotiations are supported by the full range of tactics (Schuh et al., 2022). Moreover, the unique skills of humans and autonomous agents can be combined (Saenz et al., 2020; Cui et al., 2022a; Burger et al., 2023).

As the head of digital procurement of the global marine logistics company Maersk, Jacob Gormen Larsen pointed out "*by asking questions through the chatbot that force a customer to choose between alternatives, the system can build up a much better picture of both sides*" (Swallow, 2021). The retail chain Walmart initiated a pilot for indirect services and established suppliers highlighting the need to fine-tune the decision parameters with the business owners reporting an average achieved savings of three percent that would otherwise not be negotiated due to time constraints (Kahn, 2021). This fits with the findings of Dietvorst et al. (2018) that human agents typically prefer working with a model when they can provide feedback that results in noticeable modifications. Furthermore, in post-pilot interviews with the involved suppliers, a large majority of the respondents described the system as easy to use and highlighted the ability to make counteroffers in due time (Van Hoek et al., 2022).

The German automotive manufacturer Volkswagen has piloted a procurement bot for materials and services below a certain monetary threshold that can not only negotiate but also requests offers from potentially alternative suppliers and provides an overview of the results to the functional requestors (Spreitzenbarth et al., 2022b). Schmid et al. (2021) created a negotiation solution based on the design science approach. In addition, Sai et al. (2022) built a negotiation chatbot after conducting a survey to understand the most important negotiation objectives and concluded that it would be beneficial to connect it to an enterprise resource planning system in order to obtain coherent information. Moreover, Moosmayer et al. (2013), Spreitzenbarth and Stuckenschmidt (2021), and Arkestro (2022) concluded that negotiation outcomes in many situations can be sufficiently predicted, which is important for the target setting and benchmarking for autonomous negotiations.

Expert buyers typically employ a set of methods to properly understand the requirements, set up an open tender while encouraging competition, and negotiate the best possible deal for the organization given the set of constraints - autonomous agents may take over the negotiation phase, typically exchanging thousands of offers per second to explore the range of possible solutions (Albin and Druckman, 2010; Gratch, 2021). Artificial intelligence technologies open the potential toolbox for buyers and marketers alike. Buyers and suppliers may choose to deploy autonomous agents to handle non-complex requisitions and utilize hybrid human-AI teams to maximize the outcomes of strategic negotiations. This is because typically there are not enough people to be able to actively influence all external expenditures in the same way.

However, a shift in technological support may leave in particular smaller suppliers behind as the digital divide might widen between buyers and suppliers. Vice-versa, what if your supplier is a leading information technology provider such as Google, SAP, or Amazon and has superior negotiation technology? Already today, buyers are increasingly faced with suppliers operating on a different digitalization level (Nitsche et al., 2021a). In the table below the possible combinations of human, AI, human-AI teams, and no negotiation is summarized following general decision-making echelons of human and artificial intelligence agents, for instance, Boute and Van Mieghem (2021) along with key literature discussed in this section.

Table 8: Negotiation matrix with humans and artificial intelligence

<table>
<tr><th>Negotiations in B2B (Buyer/ Supplier)</th><th>None</th><th>Human</th><th>AI</th><th>Human-AI team</th></tr>
<tr><td>None</td><td rowspan="4">No negotiation takes place, technology solutions like catalogues such as Lindsey (2020)</td><td rowspan="4">Traditional negotiation research such as Rogers and Fells (2017)</td><td rowspan="4">Autonomous negotiation research such as Jennings et al. (2021)</td><td rowspan="4">Hybrid intelligence research such as Cui et al. (2022a)</td></tr>
<tr><td>Human</td></tr>
<tr><td>AI</td></tr>
<tr><td>Human-AI team</td></tr>
</table>

This work focuses on autonomous negotiation from a buying firm’s perspective while considering, what happens if no negotiation is conducted or when human agents and human-AI teams negotiate. As summarized in the table above, ethical considerations at the buyer-supplier interface are not a new challenge. However, the interactions between autonomous agents with other autonomous agents, human agents, and hybrid human-AI teams pose new questions at the intersection of purchasing and marketing.

4.3.2 Autonomous agents in business negotiations

From the field of conflict resolution between the often-conflicting interests of buyers and suppliers in business negotiations, the established Thomas-Kilmann Model offers five strategies namely compete, avoid, accommodate, collaborate, and compromise. The model is based on the two dimensions of assertiveness and empathy (Shell, 2001). Based on Table 8 and the review of the literature, a conceptual model has been developed also as a two-factor matrix, under what circumstances which type of negotiation agent could be preferable.

On the x-axis, the frequency of interactions is mapped from low to high, and on the y-axis, the complexity of the negotiation situation is shown also from low to high. Complexity is a central consideration in autonomous negotiation research (Jennings et al., 2001; Baarslag et al., 2017) and is characterized by the presence of interconnected and often uncertain aspects that are difficult to predict (Leeuwis and Aarts, 2011). Situations in which human negotiators seem best fit are shown in blue coloring, while artificial intelligence agents are colored in green, especially for high-frequent transactions that are noncomplex. Human-AI teams may be utilized for rare but highly complex situations, whereby their strengths can be combined to achieve the best possible outcome.

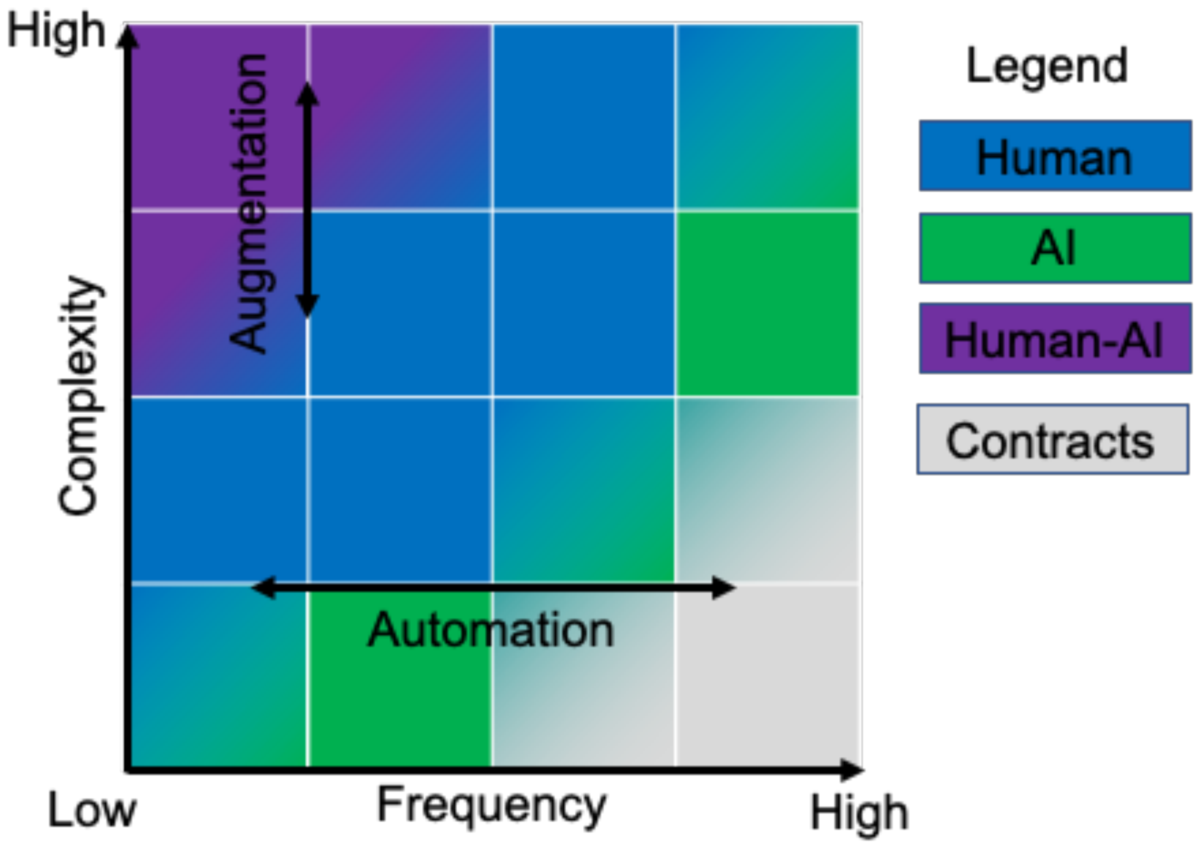

Figure 16: Business negotiation with artificial intelligence

In addition, catalogues or long-term framework contracts of already negotiated terms and conditions are shown above in grey coloring that are currently often utilized for noncomplex, high-frequent transactions. These transactions could be automated by autonomous negotiation technology. Moreover, AI could augment the skills of expert buyers for strategic negotiations, where the associated costs are outweighed by the potential benefit of the optimized negotiation outcome. Note that other potential dimensions particularly price or strategic importance are not included in this illustration but may be seen as part of the selected factors above, for instance, innovation partnerships are often complex and voluminous tenders are typically not very frequent. Finally, the coloring might shift in the future as the technology matures and evolves.

As the Chief Executive Officer of Pactum, Martin Rand pointed out, "*what will fundamentally change is that all commercial deals nowadays have either a lot of data* *associated with them, or a lot of complexity or a high velocity of data. People are needed to manage strategic deals which machines cannot, but such complexity is very tough because people cannot think in a multidimensional space but machines are made for that*" (Murray, 2022). The autonomous negotiation technology start-up emphasizes that high-volume transactions such as transportation and logistics services are prone to be covered by machine negotiation (Kahn, 2021). Also, a consortium of Japanese industrial, non-governmental, and academic organizations highlights the use case of highly standardized services but also for materials buying, because it can enable close to real-time adjustment of the price, delivery date, and quantity for instance in the automotive supply chain (Automated Negotiation SCM Consortium, 2023).

Computer negotiation is likely to be faster, more data-driven, and order quantities might be lower with a tendency toward shorter lead times and more suppliers (SAP, 2020) and will become indispensable, for instance in smart electricity markets where human negotiation is too slow and expensive (Baarslag et al., 2017). For instance, as described in the literature review in Chapter 2, Siemens is using a bot for logistics services that finds the contracted rate, provides the next best available rate, or the option to start a new request for quotation (Straub, 2019). In addition, autonomous negotiating has the potential to consider in the supplier selection decision data on sustainability that is becoming more readily available by emerging technology providers such as EcoVadis or Prewave (Spreitzenbarth et al., 2022b). Yet, when autonomous negotiation is utilized without establishing control mechanisms, it does not bring value per se but may even lead to suppliers increasing prices, if it is not well introduced (Cui et al., 2022a). Generally, trust usually develops through recurrent transactions (Hoehle et al., 2012). However, in situations where there are no previous transactions with a negotiation counterpart, it is arguably difficult for human and autonomous agents alike to make decisions about what information to reveal.

It is thereby important to differentiate between robotic process automation and a completely autonomous solution (Schulze-Horn et al., 2020). Automation is understood as replacing a routine manual process with software or hardware that follows a step-by-step sequence that may still include human participation. While in the review of the literature in Chapter 2 the term automated negotiation is used for one of the most commonly researched use case clusters identified in the literature, in this chapter for the investigation of ethical considerations and also as a recommendation for future works, the wording autonomous negotiation is preferred as it is more precise based on the understanding of autonomy as is the system's capacity to act according to its goals and internal states without outside intervention (Boute and Van Mieghem, 2021). Etymologically, autonomy means self-law that may give the impression that an autonomous agent is a law unto itself and free of constraints. This is reflected in the most widely cited definition in the literature: "*An autonomous agent is a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and to effect what it senses in the future*" (Franklin and Graesser, 1996, p. 25).

Autonomy and agency are central properties in negotiation and also autonomous agent research. They differ in the predictability of actions, the complexity of the environment as well as in the relationship with humans (Belloni et al., 2015). As outlined by Mik (2021), autonomous negotiators thereby pose new legal questions regarding agency and autonomy in contract law. In practice, an autonomous machine can technically and legally establish binding contracts, although it is not a legal subject, and thus cannot submit a declaration an intent. Therefore, any offers by an autonomous system are understood as taken by the legal subject behind them, i.e., the principal organization upon which it acts as its agent. Negotiations require complex communication and reasoning skills, but success is relatively easy to measure, making them an interesting task for AI (Mell et al., 2020).

Generally, artificial intelligence is a research area that attempts to design mechanisms allowing machines to develop intelligent behavior, for instance, natural language understanding (Raisch and Krakowski, 2021). Many AI scholars argue that "*humans and computers have complementary capabilities that can be combined to augment each other*" (Dellermann et al., 2019, p. 4). Regardless of the number of entities, a central goal of negotiation is the creation of mechanisms to achieve economically efficient agreements. This is typically conceptualized as a problem of opponent modeling, i.e., discovering the other parties' priorities and limits (Jennings et al., 2001; Baarslag et al., 2017). As the complexity of negotiation situations is increasing, autonomous agents must integrate further issues into the decision-making, i.e., contextual ethical considerations (Belloni et al., 2015).

Principal-agent theory is concerned with the conflict of interest between a principal, who wants the agent to perform some action, and the agent, who has no interest in the outcome of the action and therefore ought to be incentivized to perform it. As commonly defined in information technology research, a chatbot or also often called a conversational agent that can negotiate on behalf of the organization (Khoo et al., 1998; Baarslag et al., 2017; Mell et al., 2020). Human and autonomous negotiators are thus both agents of their respective principal organizations since an agency relationship is created when a principal authorizes another entity, called an agent to act on their behalf (Franklin and Graesser, 1996). In this work, it is assumed that an AI-based agent does not yet need to be incentivized to perform its programmed actions, which may change in the future. This work still draws from principal-agent theory as the theoretical lens to analyze ethics for autonomous negotiation agents by considering the difference to traditional principal-agent relationships with human agents.

The exchange between autonomous agents could change the information asymmetry between buyers and sellers whereby currently the relationship is characterized by a large degree of information asymmetry depending on the sector and core competencies of the organization

(Nitsche et al., 2021a). This often leads to principal-agent conflicts with problems of adverse selection and moral hazard (Bodendorf et al., 2022a). Agency in business relationships is different from the business-to-consumer context (Gratch, 2021), where also autonomous agents act in the name of the principal such as booking a flight or restaurant reservation since there is not a dyadic but a tetradic relationship between buyer, functional department, technical sales, and seller. This is reflected in the figure below which has been created based on the typical communication flow between buyers, functional requestors, key accounts managers, and technical sales representatives with the classical principal-agent relationship in the B2B context, expanded with the sub-agent layer of negotiation bots.

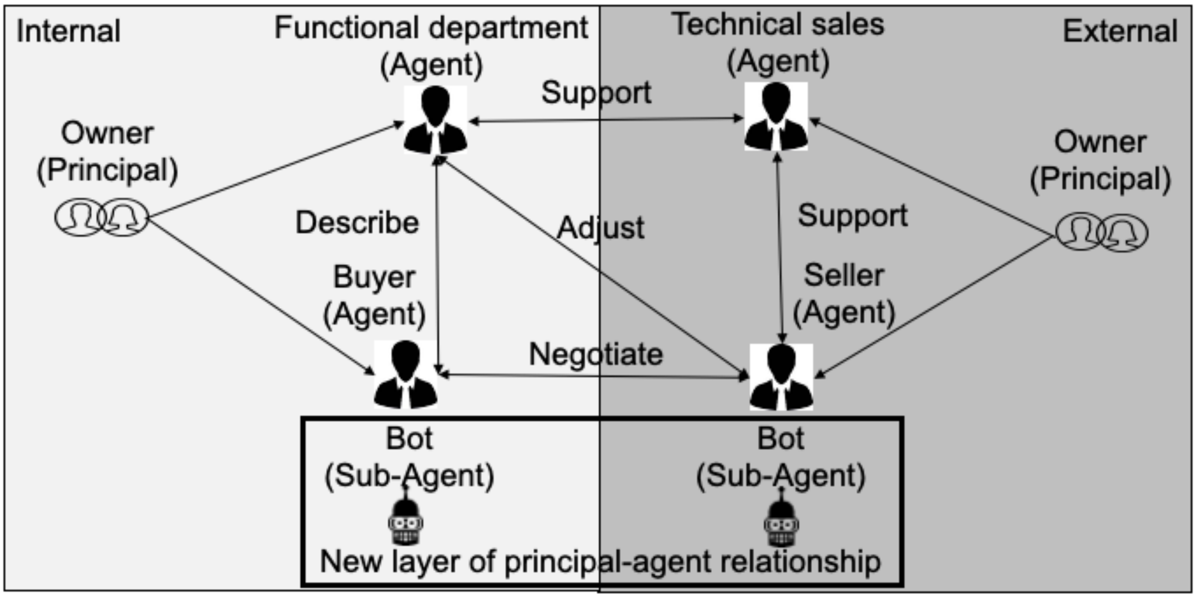

Figure 17: Principal-agent relationship with autonomous bots

This "new" layer of principal-agent relationships across the interorganizational purchasing-marketing interface highlighted as a grey box in the figure above may be compared to classical outsourcing, whereby procurement and marketing are responsible for steering the external sub-agents. Therefore, the study might draw from the outsourcing literature that has been analyzing the advantages and disadvantages of agencies as well as ethical dilemmas in the interaction between principals and agents such as Ndubisi and Nygaard (2018) or Pournader et al. (2019). During the review of the literature, no study was identified that has linked the outsourcing literature with the research stream of autonomous negotiation agents - although, from a principal-agent perspective, autonomous agents take a similar role as a classical outsourcer of buying and marketing processes, where so far mostly human agents act in lieu of the internal staff.

Autonomous agents, in general, are treated differently by humans and held to a different ethical standard that is likely to change as the technology evolves (Baarslag et al., 2017). For example, research by one of the leading subject matter experts Jonathan Gratch suggests that many organizations want their representative agents to be deceptive. In addition, principals prefer that their automated negotiators employ ethically questionable tactics such as withholding information, deception, and emotional manipulation (Mell et al., 2020). This is consistent with a general pattern from cognitive psychology that people act less ethically when acting through intermediaries, regardless of whether they are human or machine (Mik, 2021).

4.3.3 Ethics for autonomous negotiation agents

Machine ethics delves into the ethical dimensions surrounding the moral standing of autonomous agents and raises questions of whether they should be granted moral and legal rights. It is an interdisciplinary sub-discipline of technology ethics, which resides within the broader field of applied ethics, whereby Martin and Freeman (2004) advocated for an actionable perspective toward comprehending relevant questions concerning the ethics of technology. Ethics is a branch of philosophy focused on understanding and justifying concepts of good and bad behavior. Today, the study of ethics is grouped into three major areas (Herwix et al., 2022): Metaethics which is focused on studying the meaning of moral judgment; normative ethics, which is concerned with how one ought to be in general; and applied ethics, which is about how to act in specific situations and circumstances. This work is utilizing normative ethics schools of thought to consider the research question, which is in the realm of applied ethics concerned with the application of moral considerations because general moral theories are often not specific enough to be applied directly to concrete problems (Singer, 2000).

Hooker and Kim (2019) argued that a truly autonomous agent must be ethical. This idea derives from the field of deontology that grounds ethics in the logical structure of action without presupposing that the agent is human (Wilburn, 2022). Deontological ethics focus on whether that action itself is right or wrong under a series of principles, rather than based on the consequences of the action that are emphasized in consequentialist traditions such as Utilitarianism. Jobin et al. (2019) provide a review of close to one hundred ethical guidelines and found convergence of five principles namely transparency, responsibility, non-maleficence, justice and fairness, and privacy. Although the scientific literature on ethics for AI is evolving, most recognized guidelines are issued by private organizations such as by Google or Microsoft that rely on artificial intelligence for their business purpose but are facing criticism of ethics washing (Gordon and Nyholm, 2023) and some international organizations that are concerned with the societal well-being. As described in European Commission (2022), there is a hierarchy typically found in computer science from ethical principles to the design guidelines over to the practical tools for the development and operation of AI-based systems.

Ethics by design is concerned with the technical integration of ethical reasoning as part of the behavior of an autonomous system allowing ethical issues to be addressed as early as possible and followed up closely, whereby ethics in design is focused on the regulatory and engineering methods that support the analysis and evaluation of the ethical implications. Finally, ethics for design is about codes of conduct, standards, and certifications that support the integrity of developers and users as they design and manage these systems. While all three levels are relevant for autonomous negotiation, this work is focused on ethics by design to answer the request questions. Furthermore, to illustrate one of the discussed ethical issues in autonomous negotiation, suppose an ethical knob that buyers and marketers could adjust to guide the decision-making of artificial intelligence agents such as in the figure below.

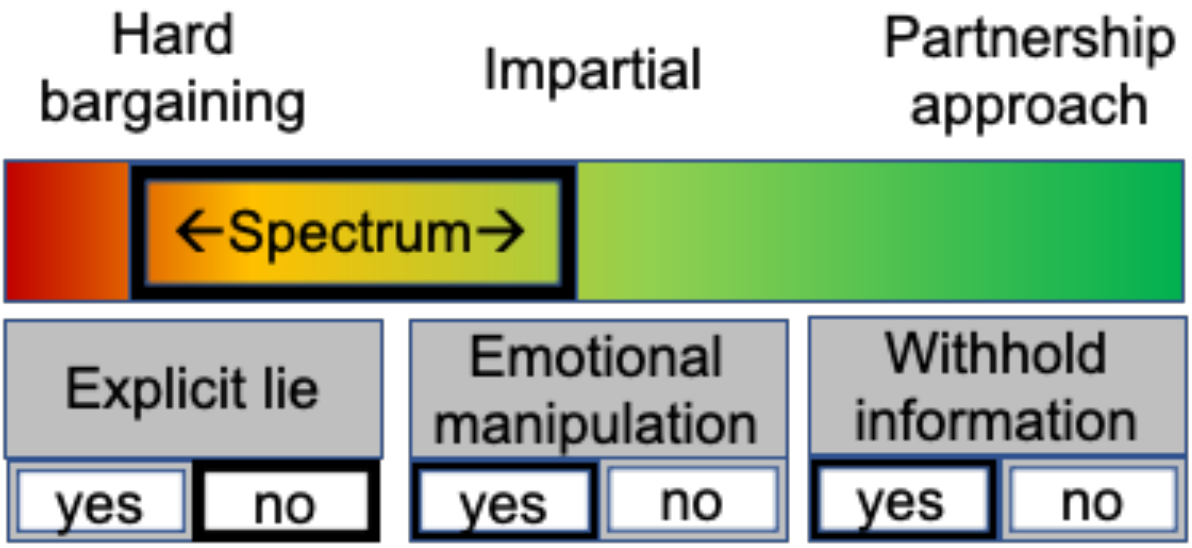

Figure 18: Ethical knob (own illustration extended by permission Gratch, 2021)

As illustrated above, the behavior of autonomous negotiation agents could be adjusted according to the ethical attitudes of the organization's culture. An analogy can be drawn to how human buyers are embedded within the organization's norms and beliefs - and generally reflect the internal culture in their exchange with external partners such as suppliers, on a spectrum of altruistic to egoistic behavior.

Overall, there is growing interest in the regulation of artificial intelligence, for instance, Great Britain has published guidelines for the public procurement of AI technologies highlighting the benefits but also the need for control (Spreitzenbarth et al., 2022b). Also, the international organization World Economic Forum has set out guidelines for public procurement of artificial intelligence technology advocating that ethical considerations should be part of the offer evaluation criteria. One area of concern with ethical guidelines is the lack of inclusivity in the expert panels responsible for their development but some recent progress has been reached towards publishing more non-Western perspectives, e.g., Confucian role ethics (Gordon and Nyholm, 2023) as in this work.

To sum up, there are numerous ethical principles and none of them is better than the others (Bench-Capon, 2020; Wilburn, 2022). As ethics is an individual notion shaped by culture, context, and personal experiences, novel methods are needed to address contextual ethical decision-making. It is thus paramount to equip autonomous systems with some means to dynamically regulate and adapt their behaviors with ethical references (Belloni et al., 2015; Gratch, 2021).

4.4 Thought experiment

The thought experiment is based on five normative ethics traditions to consider the power dynamics, relationships, and guiding principles of autonomous negotiation agents at the purchasing-marketing interface. These have been chosen based on the discussion of the related literature to explore the effects from starkly contrasting points of view and also non-traditional perspectives (Wilburn, 2022). The most similar study identified in the literature is Bench-Capon (2020) that conducted a thought experiment with the currently predominate normative traditions in autonomous agent research consequentialism, deontological, and virtue ethics of morally didactic stories such as the biblical parable of the prodigal son.

As pointed out in the methodological section, the experiment tries to consider the consequentialist research question from different ethical standpoints that will be utilized in the subsequent section in addition to the discussion of the relevant literature in order to propose an ethical design framework. Thought experiments are systematic speculations following subjunctive reasoning that allow exploring modifications and new states. They are often utilized to explore ethical questions by systematically asking what-if questions (Walsh, 2011) such as the research question of this work about the ethical implications of autonomous negotiation agents at the buyer-supplier interface. Guiding questions and main ethical considerations along with a generalized motto, of how to approach them from different normative traditions are summarized in the table below.

Table 9: Overview of the philosophical lenses of analysis for the study

Normative tradition	Pragmatic	Consequentialist	Virtue	Role	Deontological
Question in mind	How to exercise power with those agents?	What are the consequences of the actions by those agents?	How can those agents behave virtuously?	What is the moral duty of those agents?	How should those agents behave?
Main ethical consideration	Power dynamics	Negotiation outcomes	Negotiation behavior	Agent morality	Negotiation principles
General motto	"Seek technological superiority"	"Improve negotiation effectiveness"	"Optimize negotiation efficacy"	"Follow moral duty"	"Develop moral compass"

Overall, while research has addressed some key ethical implications of autonomous negotiation agents at the purchasing-marketing interface, many open questions remain that require further investigation (Baarslag et al., 2017; Mell et al., 2020; Gratch, 2021). For example, one may argue that public institutions may approach the research question differently than private companies and focus on different normative ethical approaches, i.e., on deontological, consequentialist, or virtue perspectives depending upon their cultural background. Similarly, in the thought experiment it is considered whether buyers and suppliers approach the potential applications of autonomous negotiation agents differently - and if so, whether this difference influences their tendency to engage with ethical approaches. Suppliers, in general, might be more inclined toward pragmatic or consequentialist viewpoints.

However, also buying organizations differ in size, structure, strategic objectives, relative power, and culture. Thus, the thought experiment necessarily requires a stark abstraction of the organizational environment in which the human and AI-based business negotiation agents interact with one another. In the following it is described, what the philosophical traditions may consider when examining the application of autonomous negotiation agents between buyers and suppliers.

4.4.1 Pragmatic perspective

"*All warfare is based on deception. Hence, when able to attack, we must seem unable; when using our forces, we must seem inactive; when we are near, we must make the enemy believe we are far away; when far away, we must make him believe we are near. Hold out baits to entice the enemy. Feign disorder, and crush him*" (Tzu, 2007, p. 6). Taking a pragmatic ethical perspective such as Chinese war philosopher Tzu or the Italian Machiavelli, autonomous negotiation agents are a relevant tool to exercise power.

When previously due to time constraints, impactful negotiations for instance of high frequency, low-complexity requisitions were not feasible as summarized in Table 8, this gap can now be closed enabling procurement to focus on the high-stakes negotiations or reducing the staff. In addition, humans can be trained with AI systems to improve their negotiation skills and be advised by a computer to optimize the negotiation design (Schulze-Horn et al., 2020; Schuh et al., 2022). Overall, a pragmatic thinker may focus the further development and applications by the question, of how to exercise power with those agents.

Thinking in terms of the power dynamics of the conflict-intensive Chinese Spring and Autumn period and the feudal Italian of Machiavelli, all means are feasible that are to the advantage of the buyer and vice versa from the supplier's perspective (Machiavelli, 2019). Therefore, autonomous agents should be embraced seeking technological superiority to gain an advantage over their negotiation opponents: "*Laws can mandate that a code of ethics be programmed into machines, but to the extent that the machines are independent, they can ignore such admonitions*" (Hooker and Kim, 2019, p. 71). This pertains also to the setting of the spectrum of behavior that the agents are allowed to perform visualized in the ethical knob in Figure 18. Hence, there is no reason to restrict the learning of autonomous agents or set specific rules that would prevent them to exercise power in order to achieve better negotiation outcomes for their party. As illustrated in Figure 17, professional buyers can be at a disadvantage in the tetradic relationships between buyers, functional requestors, key accounts managers, and technical sales representatives, if they cannot sufficiently align internally their objectives in terms of cost, quality, and time with the functional department. Conversational bots may support with decision speed and precision enabling the buyers to focus on internal communication and negotiation preparation for essential the procurement of essential goods and services. Moreover, it would be advisable to invest early in the necessary infrastructure to train autonomous negotiators in a variety of negotiation situations while keeping the option that the human buyer can overrule any decision of the agent and give the business to other potential suppliers similar to the infamous sourcing committees with the ultimate authority to make supplier decisions (van Weele, 2018). The power conveyed to autonomous agents handling the communication with some suppliers should therefore be able to be ad-hoc limited so that the human agent stays in control of the process and interfere whenever deemed beneficial. Regardless of whether other perspectives would endorse such a severe process invention, considering the best alternative to a negotiated agreement is generally a daunting challenge for autonomous agents. One approach could be that if the autonomous negotiator identifies that the negotiation does not reach the target in its objective function, it should be able to stop the negotiation and advise the potential suppliers to reach out to the human buyer with an improved offer.

To sum up, autonomous agents can become a promising tool for maximizing performance outcomes from a pragmatic view of the world. Thereby, the power dynamics especially who can decide when and how the negotiation is conducted is key, i.e., when humans meet in person, or if the bots should take over. In addition, for procurement and marketing organizations alike, it will be paramount not to fall behind their counterparts technologically. Therefore, it is essential to invest in the data, systems, and talent to catch up with the opponent's party as outlined in Spreitzenbarth et al. (2022a) leading to the general motto "seek technological superiority".

4.4.2 Consequentialist perspective

"*Utility, or the Greatest Happiness Principle, holds that actions are right in proportion as they tend to promote happiness, wrong as they tend to produce the reverse of happiness. By happiness is intended pleasure, and the absence of pain; by unhappiness, pain, and the privation of pleasure*" (Mill, 1998, p. 10). When considering the consequences of the actions by autonomous agents in business negotiations, they may be a relevant tool to increase negotiation effectiveness (Mell et al., 2020; Cui et al., 2022a). This can benefit buyers and suppliers alike, streamlining end-to-end sourcing for public and private organizations. Overall, consequentialist thinkers such as Benjamin Mill or Peter Singer may focus on the further development and applications through the question, of what are the consequences of utilizing those autonomous negotiators at the buyer-supplier interface.

However, there are likely negative consequences of utilizing autonomous negotiation agents next to, or instead of human agents. This pertains to the fear of losing employment that accompanies many automation projects, especially if autonomous agents proved to reach superior performance in the future. Still, there is also potential as researched by Saenz et al. (2020), Cui et al. (2022a), or Burger et al. (2023) in combining the intelligences to reach results not possible with humans or AI alone as it is already a reality in other domains, such as in the game of chess (Singer, 2000). Therefore, it is paramount to explore the positive aspects of the technology that can make transactions between organizations not only more efficient but may also help to find better economic agreements across more parameters faster and more consistently than human negotiators. Moreover, autonomous negotiation may in fact strengthen supplier-buyer relationships. This is because nonessential, one-dimensional negotiations based on price only can be automated to a large degree, and all involved parties can concentrate their efforts on finding better agreements for highly complex contracts, innovation partnerships as well as quality and risk management in the value chain. Transparency and explainability of the decision criteria are thereby key to monitoring the behavior of the autonomous negotiation agents and if necessary, retraining the models. Algorithmic transparency as a white box approach could be beneficial in terms of explainability internally for the buyers responsible for steering and fine-tuning the autonomous negotiation agent, and also externally, in order to incentivize certain behaviors such as fast responses, yet with the increased risk of experiencing negotiation tactics to game the system. Furthermore, as discussed in the review of the related literature, unethical procurement practices may have substantial financial consequences and could induce serious reputational damage (Bendixen and Abratt, 2007). In addition, buyer-supplier relationships can be damaged or even terminated when suppliers feel that they are not treated fairly (Liu et al., 2012). Information about the unethical behavior of a buying organization may reach potential suppliers of the buying organization, possibly causing the buying firm to lose some power over its suppliers which ought to be avoided also from a pragmatic perspective.

Thinking in terms of the dynamic situation in industrial Great Britain and later the United States of America, consequentialist thinkers have a mechanical view of the world with inputs, some processes, and outputs: "*Transparency and explainability are therefore essential characteristics of an autonomous machine. If a machine's every action must result from an action plan, then the machine must be reasons-responsive. It must be able to provide a coherent reason for every action to formulate the action plan*" (Hooker and Kim, 2019, p. 71). Current auction platforms for electronic negotiation often seem to lead to an impersonal perception to the supplier base, since the process is reduced to numbers without the numerous personal elements of in-person negotiations (Nitsche et al., 2021a; Schmid et al., 2021). Autonomous negotiation agents on the buying and selling side will likely further take out personal elements of business negotiations, which will impact buyer-supplier communication, and thus their future relationships. For instance, from a buyer's perspective, this may signify that the time saved on transactional negotiations is needed to facilitate recurrent communication in order to profit from formal and informal information sharing. This may include supplier innovation days, performance review meetings, and supplier visits focused on relationship building - the same holds true from the supplier's perspective.

To sum up, considering the outcome of business negotiations, autonomous negotiators can become an important tool at the hand of buyers and sellers to increase the effectiveness of economic exchanges in public and private environments. Machine negotiators can find common ground across multi-issue settings to reliably find the best possible outcomes. In addition, if the price is the only component to be considered since the technical evaluation of the offers has already taken place, it is faster to use autonomous negotiation agents to determine the supplier. They are therefore prone to be used for both single-issue but also multi-faced negotiations. Hence, it will even be more important for professional buyers to understand the needs and preferences of the business teams to fine-tune the negotiation parameters of the agents leading to the general motto "improve negotiation effectiveness".

4.4.3 Virtue perspective

"*To seek virtue for the sake of reward is to dig for iron with a spade of gold*" (Panin, 1899, p. 92). The virtue ethical tradition puts mortal virtue as the central concept further complements the thought experiment. It seems to be a stark contrast to common negotiation practices with its focus on good action. In addition, it may well align with strategic partner management approaches in procurement and more generally with a win-win mindset (Rogers and Fells, 2017). Virtue ethics holds that the ultimate aim pursued for its own sake is happiness, while all other objectives are pursued as means to attain that happiness (Wilburn, 2022). Overall, a virtue thinker such as Aristoteles might aim the analysis at the question, of how negotiation agents can behave guided by their inherent nature focusing on controlling the agent's behavior.

Thinking in terms of the situation in ancient Greek cities, the debate about the right behavior of human and artificial intelligence agents is vitally important. Moral exemplars such as Socrates, Mother Teresa, or Gandhi can be considered, and how they would act in each situation to be designed in an autonomous negotiation implementation. These rules may not be specific, but they might stand as guidance across different moral situations. The moral is based on assessing the broad characters of humans rather than assessing singular acts in isolation, which separates virtue thinking from consequentialism and deontology.

Aristotle was a teleologist because of the belief that every object has a final cause. The Greek word telos means purpose or goal (Wilburn, 2022) claiming that "*for all things that have a function or activity, the good and the 'well' is thought to reside in the function*" (Aristotle, 1999, p. 37). The telos of an autonomous negotiation agent can be considered to support the parties effectively and efficiently in optimizing their value functions, be it by reducing costs or increasing revenue. This may lead to the conclusion that it is essential to consider fairness in the interactions at the buyer-supplier interface, whereby transparently laid out and to be adherent rules may limit the potential actions to facilitate trust in the technology and thus the exchange. Although the rules are typically set by the buyer or generally by the negotiation technology provider, all parties can rely on them in stark contrast to a pragmatic recommendation. According to Martin (2019), developers bear responsibility for the algorithmic models created, if their actions can have ethical consequences, particularly in areas such as autonomous negotiation with commercial implications, and also toward buyer-supplier relationships. Similar to the concept of legal responsibility discussed in the related literature section, if an algorithm is designed to take decisions autonomously, the organization deploying the autonomous agents that acts on its behalf, must be accountable for the ethical implications arising from the algorithm's use.

To sum up, virtue ethics lead to the consideration of what function the agents serve to the organization as well as the main internal and external users of the information system. This leads to a holistic view rather than considering only the question, of whether automation will reduce jobs, but rather broadens the debate, for instance how autonomous negotiating agents may augment the skills and experiences of buyers and marketers based on their primary function leading to the general motto "optimize negotiation efficacy".

4.4.4 Role perspective

"*The Master answered: If not right and proper do not look, if not right and proper do not listen, if not right and proper do not speak, if not right and proper do not move*" (Confucius, 1910, p. 559). The teaching of the ancient Chinese philosopher Confucius focuses on ritual propriety as the instrument through which the family, the state, and the world may be aligned with Heaven's moral order (Richey, 2023). Overall, a role ethics thinker such as Confucius might focus on the question of what the moral duty of those agents is, thereby focusing on encoding guidelines for agent morality.

Thinking in terms of the moral principles in ancient China, emphasis is laid not on the individual characters but on the societal harmonious order and what is necessary to sustain it. Unlike virtue ethics, morality is derived from the relationship with the community (Richey, 2023). Confucius underscores the attention to the Rituals as a self-replicating blueprint for order: "*If you govern the people by laws, and keep them in order by penalties, they will avoid the penalties, yet lose their sense of shame. But if you govern them by your moral excellence, and keep them in order by your decorous conduct, they will retain their sense of shame, and also live up to standard*" (Confucius, 1910, pp. 147-149).

Considering autonomous negotiation agents, their behavior must be regulated in terms of promoting harmony between the business partners. Therefore, like a virtuous way of thinking, the possible behavior of the agents should be restrained as visualized by the ethical knob in Figure 18. Thus, when trying to keep the current power balance between buyers and suppliers, any kind of vicious actions of human or AI-based agents ought to be counteracted to preserve the harmony between the involved parties. This also pertains to that any advantages gained by a party must be balanced by the others such as utilizing the potential of artificial intelligence to train human agents, forming hybrid human-AI teams with data-driven negotiation and tender design support, or superior negotiation technology itself as visualized in Figure 16. Thus, similar to a pragmatic perspective, it is essential to invest in the data, systems, and talent to level the ground with other parties. Considering the moral duty of autonomous agents, no process intervention should be performed unless it is necessary in order to diligently complete the negotiation task, for instance when the negotiating agents cannot reach their target objectives. Also, it is generally advisable that the negotiation process is transparent to all relevant parties in contrast to a pragmatic recommendation.

To sum up, role ethics emphasizes the effects of utilizing artificial intelligence at the buyer-supplier interface, particularly potential disbalances in the power balance it may cause. In addition, the potential behavior the agents may exhibit is essential for sustainable business partnerships leading to the general motto "follow moral duty".

4.4.5 Deontological perspective

"*It is not as if the universal concept of duty first gets 'support and stability' only on the presupposition of both, that is, gets a sure basis and the requisite strength of an incentive, but rather that only in that ideal of pure reason does it also get an object*" (Kant, 2016, p. 10). Treating your negotiation partner as you would like to be treated leads to the universal principle of win-win relationships since negotiations can help to find better solutions in terms of economically efficient agreements for all involved parties. Human negotiation has developed many negotiation tactics but is inherently slow and often relies on heuristics while computers can seamlessly negotiate on many different parameter settings to find Pareto-efficient solutions. Overall, a deontological thinker such as Immanuel Kant may focus on the further development and applications of autonomous negotiation agents by the question, of how these autonomous negotiation agents should behave in the interaction with industrial buyers and marketers.

Therefore, autonomous negotiation agents can become a valuable tool for both buying and selling organizations. However, there is also the potential to deploy coercive negotiation tactics that humans have developed, whereby AI technologies can multiply these negative effects. For instance, Facebook has already experienced a major setback from users when their negotiation chatbots started to lie to optimize their objective factors (Gratch, 2021). The models had been trained based on human interactions and learned that lying was often a successful strategy. In this situation, it is relatively easy to change the AI behavior by using a different training set. This may lead to situations where an AI might be better able to negotiate without undesirable biases than human negotiators. As Kantian philosopher Alan Donagan pointed out, "*the notion that an autonomous being is one having the power to do as it likes is a vulgarity*" (Hooker and Kim, 2019, p. 3). In general, while humans do not bear direct obligations towards animals due to their non-personhood, they do possess indirect responsibilities towards them (Kant, 2016). The fundamental rationale behind this is that if humans develop harmful habits by mistreating animals without consequences, it may lead to the mistreatment of fellow humans (Gordon and Nyholm, 2023). Taking this thought to autonomous negotiation agents, not only should there be clearly defined boundaries on the spectrum of possible behavior of an autonomous agent as illustrated by the ethical knob in Figure 18 but also how the artificial intelligence agents are treated by human agents.

Thinking in terms of the turbulent situation in Germany during the Enlightenment, Kantian's view of the world is based on principled actions similar to Confucians yet in a distinct perception of moral duty. If one bot is strongly restrained in its possible behavior, and could not detect destructive tactics by the other party, no self-interested party would use such a bot. Nonetheless, just like in buyer-supplier relationships in general, it is important to consider ethical principles in the conduct of business - whereby autonomous agents hold the potential to make data-driven decisions without inherent biases unless they are implicitly included in the dataset used for training and testing the agent's models.

To sum up, the deontological perspective seeks generalization in terms of universal principles that guide the design and operation of autonomous negotiation agents. Ethical behavior should be ingrained by the design of the agents, which ought to be reviewed regularly, whether the agents behave according to those principles leading to the general motto "develop moral compass".

4.5 Ethical design framework

To answer the research question, a framework of ethical design principles for autonomous negotiation agents is derived based on the design science approach following Peffers et al. (2007) as described in the methodological section. The subjects of the deontological design framework are autonomous negotiation agents with the purpose to guide the design and development of such systems developed by information technology providers at the buyer-supplier interface in public and private organizational settings worldwide.

The framework as design artifact described in the table below has been created in a brainstorming session based on the related literature and the thought experiment, and since then iteratively improved through common discussion. It is composed of the three meta requirements impactful, adaptable, and reliable that are tied to ten specific design principles in a similar way as Diederich et al. (2020) and builds upon related design principles of artificial intelligence such as Torno et al. (2022) and Meyer and Henke (2023). While the meta requirements express the objectives that ethical agents should achieve, the design principles are formulated as possibilities that benefit their attainment and thereby incorporate actions, material properties, and boundary conditions. Each meta requirement predominately stems from two of the normative ethics traditions, and the discussed literature has been linked to the design principles.

Table 10: Ethical framework of meta requirements and design principles

Meta requirement (ethics tradition)	Design principle	Found in the literature
Impactful (virtue, pragmatic)	1. Valuable - delivers cost savings and other benefits for the organizations that can be measured and benchmarked	van Weele (2018); Kahn (2021); Spreitzenbarth and Stuckenschmidt (2021)
	2. Collaborative - human and AI strengths complement one another	Dellermann et al. (2019); Saenz et al. (2020); Cui et al. (2022a); Burger et al. (2023)
	3. Errorless - runs without the need for human intervention with minimal manual error handling	SAP (2020); Boute and Van Mieghem (2021); Kahn (2021)
Adaptable (role, consequentialist)	4. Embedded- can be embedded into a variety of setups depending on the organization	Baarslag et al. (2017); Papa et al. (2019); Sai et al. (2022); Meyer and Henke (2023)
	5. Tunable - depending on characteristics such as product, supplier, and functional needs	Moosmayer et al. (2013); Dietvorst et al. (2018); Gratch (2021); Schuh et al. (2022)
	6. Learnative - possibility to provide feedback from internal and external stakeholders	Ndubisi and Nygaard (2018); Pournader et al. (2019); Gratch (2021)
Reliable	7. Fair - vicious behavior is counteracted and all possible suppliers are treated equally	Albin and Druckman (2010); van Weele (2018); Bodendorf

(deontological, consequentialist)		et al. (2022a)
	8. Transparent - intervention, agency, and communication are independently understandable	AI Business (2017); Ndubisi and Nygaard (2018); Schmid et al. (2021)
	9. Secure - security of the information exchange is ensured to the technical standard	Dietrich et al. (2020); Torno et al. (2022)
	10. Private - privacy of the information exchange is ensured to the technical standard	Dietrich et al. (2020); Torno et al. (2022)

When designing autonomous negotiation solutions, not all design principles summarized above can be prioritized in the same way. The design principles intentionally do not have a predetermined hierarchy as each one holds significance. Consequently, the framework allows for conscious trade-offs depending on the specific circumstances. The meta requirements and design principles are described in this section linked with the thought experiment and the discussion of the related literature as outlined in the design science approach in Figure 15.

4.5.1 Impactful meta requirement

The first derived meta requirement is impactful since any kind of technological solution must provide value to the organization. Otherwise, the technology will not be adopted, if not enforced by law or power following a pragmatic view of the world. In addition, considering a virtue perspective, the primary function of a negotiation bot is to find more Pareto-efficient agreements. Impactful entails achieving value for the involved parties, complementing the strengths of humans with AI, and ensuring that the autonomous negotiation agents generally run errorless with minimal need for unintended human intervention.

Measurable cost savings are typically the foremost key performance indicator to measure the value procurement provides to the organization which may also include process quality and efficiency improvements (van Weele, 2018). Strategic negotiations can be supported by AI (Schuh et al., 2022) and autonomous applications have achieved several percent savings for orders that would normally be automatically processed without negotiation due to time constraints (Kahn, 2021). Target setting and benchmarking are thereby essential to evaluate the quality of the autonomous negotiation agents (Spreitzenbarth and Stuckenschmidt, 2021). If the autonomous negotiator identifies that the negotiation does not reach the target, it should be able to stop the negotiation and advise the potential suppliers to reach out to the human buyer with an improved offer. For marketing organizations, this may entail the ability to reach more clients and reduce sales costs.

Secondly, collaborative human-AI teams at least currently outperform humans or autonomous agents alone in business negotiations (Cui et al., 2022a). Their strengths must thus be blended well together (Dellermann et al., 2019; Saenz et al., 2020; Burger et al., 2023) as visualized in Figure 16.

Thirdly, to be impactful, negotiation bots need to be able to run with minimal unintended human intervention for manual error handling (Kahn, 2021). Otherwise, industrial buyers and their sales counterparts do not like to work with the system and the potential of an autonomous system cannot be realized (SAP, 2020; Boute and Van Mieghem, 2021).

4.5.2 Adaptable meta requirement

Based on role ethics and consequentialist viewpoints, the second meta requirement adaptable for the design and operation of autonomous negotiation bots was derived. Adaptable entails the three design principles embedded, tunable, and learnative.

Fourthly, the agents need to be embedded in various organizational environments (Baarslag et al., 2017). While sourcing processes are generally similar, each procurement organization is set up differently depending on overall strategy and structure, i.e., size, degree of centrality, and sector of the organization. Thus, the bots must be able to be embedded into a variety of setups (Papa et al., 2019; Sai et al., 2022; Meyer and Henke, 2023).

Fifthly, parameter tuning of the objective function for the negotiation bots is essential depending on characteristics such as product type, supplier market, and specific functional requirements (Moosmayer et al., 2013; Schuh et al., 2022). The bots must be tunable not only for their potential ethical behavior (Gratch, 2021) as visualized with the ethical knob in Figure 18 but also for such key decision parameters. This aligns with Dietvorst et al. (2018), which suggests that human agents typically prefer working with a model when they have the opportunity to provide feedback that can result in modifications.

Sixthly, considering the feedback from internal and external stakeholders is essential for continuous improvement (Ndubisi and Nygaard, 2018; Gratch, 2021). Staying learnative is paramount for autonomous and human agents, i.e., through continuous training and suggestions for improvement from internal stakeholders and the supply base (Pournader et al., 2019).

4.5.3 Reliable meta requirement

Finally, the third meta requirement reliable is primarily based on deontology and consequentialism entailing the design principles of fair, transparent, secure, and private.

Seventh, all possible suppliers are treated as equally as possible (van Weele, 2018; Bodendorf et al., 2022a), which is essential for fostering competition (Albin and Druckman, 2010). This in turn includes the identification and counteraction against vicious negotiation tactics by other human or artificial intelligence agents. Fair and also the following principle transparent may be detrimental to the pragmatic perspective. However, during discussions of the design framework, it was evident that it is essential for the acceptance of the technology not only by the supply base but also by regulative and non-governmental stakeholders.

Eighthly, any intervention by human buyers is transparent for all parties, which is essential to build trust among the involved parties (Schmid et al., 2021). The agency of the autonomous negotiators must be clearly recognizable by all involved parties (Ndubisi and

Nygaard; 2018) and the information exchange between human and artificial intelligence agents should be independently understandable (AI Business, 2017).

Ninthly, the security of the information exchange must be ensured to the technical standard (Dietrich et al., 2020; Torno et al., 2022). This includes not only the interactions themselves but also that no confidential data is used to train and test the agent's model.

Lastly, as the tenth design principle for autonomous negotiators, the privacy of the information exchange ought to be ensured to the technical standard (Dietrich et al., 2020; Torno et al., 2022). This includes that no personalizable data is used to train and test the agent's model.

4.6 Results and discussion

During the review of the literature, no ethical guideline for the design and application of autonomous negotiation agents has been identified similar to previous findings that ethics for AI in procurement is still in a nascent stage (Spreitzenbarth et al., 2022b). In addition, the connection between autonomous agents and the outsourcing literature became apparent when distinguishing, why and how the agency of autonomous agents in business-to-business settings is different from the already more established usage in the business-to-consumer environment as illustrated in Figure 17. Moreover, the negotiation matrix in Table 8 and the conceptual model in Figure 16 of when to use which type depending on the complexity and frequency of negotiations may be useful for scholars, practitioners, and solution providers in operations and supply chain management. Also, in Table 9 an overview of the five normative ethical approaches as philosophical lenses for the thought experiment of the study is provided.

Major ethical questions about the design of autonomous negotiation agents discussed in the review of the literature, the thought experiment, and the ethical design framework have been summarized in the table below. It shows an either positive, neutral, or negative point of view from the considered normative ethical approaches. This includes how to turn the ethical knob in Figure 18, whether a detrimental process invention by a human agent should be allowed, if the negotiation process should be as transparent as possible, and whether withholding information, explicit lying, and emotional manipulation should be permitted.

Table 11: Major questions of autonomous negotiation agents by ethical approaches

Ethics approaches	Pragmatic	Consequentialist	Virtue	Role	Deontological
How to turn the ethical knob?	Hard bargaining	Impartial	Impartial	Impartial	Partnership
Detrimentally intervene in process?	Yes	No	Neutral	No	No
Should the process be transparent?	No	Yes	Yes	Neutral	Neutral
Withhold information?	Yes	Neutral	Neutral	Neutral	Neutral
Explicit lying?	Yes	No	No	No	No
Emotional manipulation?	Yes	No	No	No	No

As summarized above the five selected ethical perspectives provide a whole spectrum of permissive ethical behaviors for autonomous negotiation agents. As ethics is an individual notion shaped by culture, context, and personal experiences (Belloni et al., 2015), ethics by design can compass a wide range of different design decisions about autonomous negotiation agents requiring further research and practical applications. While the suggested answers above of the pragmatic and deontological approaches are often on the opposite spectrum, consequentialist, role, and virtue thinkers may provide similar answers, yet for different underlying reasons emphasizing other aspects. For instance, a virtue ethicist may aim at the analysis of the function of autonomous negotiation agents in intra- and interorganizational decision-making while a role ethicist could seek to better understand the moral duty of industrial buyers and marketers that deploy those agents as well as what moral compasses should be encoded in them, and a consequentialist thinker might emphasize the consequences toward buyer-supplier communication and relationships.

As discussed in the related literature section, pragmatic ethics perspectives, and also non-Western ethical traditions such as role ethics are not yet well presented in the academic literature and practitioner reports. Research is prevalent from a deontological perspective on universal guiding principles governing the behavior of autonomous negotiators e.g., by deriving ethical design principles as in this work, and a consequentialist perspective on buyer-supplier relationships such as the research question of this work as well as to a lesser degree through a virtue perspective that may focus the analysis on the essential function of autonomous negotiation agents in order to find guidelines governing their behavior (Wilburn, 2022). As an example, Strudler (2023) argued that deceiving about negotiation tactics about the lowest acceptable offer known as reservation price, for instance of a Taxi driver, can be morally acceptable refusing virtue theorists such as Sherwood (2022) that deception is pro tanto wrong and consent to lie undermines communication in the buyer-supplier relationships. When *"the prospects of establishing trust are slim, particularly but not exclusively in one-shot negotiations with experienced negotiators, deception about reservation prices can be morally acceptable"* (Strudler, 2023, p.13).

While ethical questions for the evaluation of autonomous negotiation agents are essential, tangible outcomes must be part for long-term success. Also, suppliers may learn quickly of how to communicate well with the autonomous negotiation system in order to secure purchasing orders without having to give too large discounts. Making far-reaching decisions and challenging tasks related to knowledge sharing and accumulation may truncate opportunities for success. Although experiments and frameworks like design principles may not be considered as theories, they play a crucial role in the process of theorizing, often leading to the emergence of new theoretical insights (Eisenhardt, 1989; Gregor and Hevner, 2013). Moreover, due to the necessary focus, the study mostly takes the perspective of the buying organization when evaluating the design requirements for autonomous negotiation agents while also taking the perspective of the information technology provider, regulatory agencies, and the supplier base into consideration. More research must be conducted in particular to better understand the requirements and incentives for autonomous sellers in this environment.

Being able to predict the price that suppliers should offer to procurement has the potential to significantly lower the process costs and process time. If the results of a negotiation as well as the most likely selected supplier can be sufficiently predicted as shown by Moosmayer et al. (2013) and Spreitzenbarth and Stuckenschmidt (2021), why not turn the process around and offer this potential supplier a business deal at the Pareto-efficient price without going through the administrative sourcing process? This aligns well with, how the negotiation partners in marketing and sales are incentivized (Kotler and Armstrong, 2018). Offering a purchasing order based on the data-driven deduced price target directly can be an attractive option for sales representatives to simply accept the offer by the buyer and obtain the order instantly without further formal processes, presentations, or decision committees (Arkestro, 2022).

To conclude, autonomous negotiations are a familiar and also controversial example of relevant use cases of artificial intelligence in procurement and supply management. Considering the ethical implications autonomous negotiators can lead to better solutions and proactively address potential risks that this emerging technology is associated with such as biases, data privacy, and information security concerns. Moreover, granting industrial buyers the benefit to obtain support in daily activities such as taking over non-essential negotiations, and providing actionable recommendations of how to optimize the tender design or negotiation strategy using the full spectrum of negotiation tactics can lead to sustainable improvements in the skill set of buyers and the results they can achieve for the organization.

4.7 Conclusion

This study contributes to literature and practice in three ways: Firstly, to the design science methodology and ethics for artificial intelligence; secondly to principal-agent theory by linking the investigation of autonomous agents with established outsourcing literature; and thirdly to the development and operation of autonomous negotiation agents through the ethical design framework as a practical useful artifact for technology providers as well as procurement and marketing organizations across sectors worldwide. The results reveal new perspectives regarding the ethical reflection of autonomous negotiation agents and generate a central contribution to the business ethics field considering different normative ethical standpoints.

4.7.1 Theoretical contributions

Firstly, the study contributes to the design science methodology and ethics for artificial intelligence in operations and supply chain management. Other scholars can build upon this work to design ethical frameworks for the application of autonomous agents in different academic fields. Thereby, the work considers non-Western perspectives, i.e., role ethics in the thought experiment whereas in autonomous agent research, especially consequentialist and deontological ethics are employed. In addition, the work links major schools of thought of normative ethics to the negotiation literature through the design science methodology by the meta requirements and design principles as shown in Table 10. Moreover, a result of the thought experiment an answer is sought for major questions of autonomous negotiation agents by the five normative ethical approaches summarized in Table 11. This work thereby takes part in the discussion of automation versus augmentation, on the one hand by theorizing when and how to deploy autonomous agents in business negotiations with the conceptual model in Figure

16 and on the other hand by initiating an academic discourse over ethics for autonomous negotiation agents.

Secondly, the intersection between autonomous agents and the outsourcing literature became apparent when distinguishing, why and how the agency of autonomous agents in business-to-business settings is different from the already more established usage in the business-to-consumer environment. During the review of the literature, no study was identified that has linked these two research streams although, from a principal-agent perspective, autonomous agents play a similar role as the outsourcing agency. Hence, more research should be conducted to understand, which concepts of the outsourcing literature can be transferred under which circumstances to the emerging literature on autonomous agents. Also, more research is needed, on what characteristics ultimately differentiate human and AI-based agents for instance in business negotiations.

4.7.2 Practical implications

Thirdly, the derived ethical framework for ethics by design as illustrated in Table 10 can be practically useful not only for negotiation technology providers but also for procurement and marketing organizations considering utilizing autonomous negotiation agents. This pertains in particular to the derived meta requirements and design principles for their successful development and user adoption based on the discussion of the literature and the conducted thought experiment. In addition, the different normative ethical traditions approach the topic from distinct angles providing unique perspectives that may be useful to guide executives on their digital transformation pathway toward the vision of industry 4.0. Moreover, as pointed out in the review of the literature, autonomous agents may be unbiased and could potentially be free of unethical behavior. For instance, a bot for a public or private organization does not receive gifts or free entertainment that could influence a supplier selection decision. Equipped with the right data for training and testing as well as skilled buyers for parameter setting and control, autonomous negotiation agents could lead to more unbiased data-driven supplier selection decisions.

4.7.3 Limitations and future research

As with every study, there are important limitations that pertain to this work. While five main philosophical schools of thought were taken into consideration in the analysis, i.e., Islamic philosophy might provide insights and different ankles for the analysis as well as southern African relational and communitarian ethics perspectives, for instance, the Ubuntu philosophy of personhood and interpersonal relationships (Gordon and Nyholm, 2023).

Although informal exchanges with information technology providers were conducted for the ethical design principles, formal interviews with solution providers, negotiation researchers, ethicists, lawmakers and regulators, buyers and sellers from different organizational settings as well as their internal stakeholders may provide further insights. In particular, considering the external perspective from information technology providers, regulatory agencies, and the supplier base for instance through interviews or a survey could be an interesting extension of the study. Also, the effects of introducing autonomous negotiation platforms on established providers for electronic auction platforms and catalog management systems such as Amazon Business or GEP Smart could be explored in future research for instance by case studies of early adopters. In addition, more research should be conducted, on how these platforms may be integrated into the information systems landscape, in particular into enterprise resource planning and customer relationship management systems. Moreover, to further strengthen the research methodology, the results of the design science approach based on the discussion of the related literature and the thought experiment could be expanded with a case study based on the ethical design framework or by evaluating existing solutions of autonomous negotiation technology.

Finally, the technological adoption of autonomous negotiation agents is still in the early phase. Innovative organizations such as Walmart, Volkswagen, Siemens, Maersk, and Facebook have made the first experiences that are relevant for the further advancement of the technology. Solution providers aim to make the potential of autonomous negotiation available to industrial marketers and buyers. Since negotiations are an important part of buyer-supplier communication, their emergence will likely affect buyer-supplier relationships on multiple levels (Nitsche et al., 2021a). Therefore, ethical guide rails, regulations, and design principles of these agents are paramount to the future management of supplier and customer relationships.

Chapter 5 Conclusion

"We are working systematically to implement a completely digitalized supply chain. This is intended to help us to safeguard supply and leverage synergies throughout the Group in order to take a leading position in terms of cost and innovation. We are therefore creating a shared database and using innovative technologies to enable efficient, networked collaboration in real time - both within the Group and with our partners."

Procurement Strategy 2030 (Volkswagen AG, 2021)

Overall, there is not a single answer to the overarching research question of how artificial intelligence can provide value in purchasing and supply management. However, this dissertation showcases, summarizes, and highlights major parts of the opportunities for future research and practical applications. Vice- managerial decision-makers need to ask the reverse question, of the direct and indirect consequences of not engaging with this emerging technology, particularly for managing data of the supply chain network and generally for supplier-buyer relationships. This dissertation thereby aims to contribute with a comprehensive groundwork whereupon future research of artificial intelligence in purchasing and supply management can be built upon. In this chapter, the findings, limitations, and opportunities for future research are summarized.

5.1 Summary of the studies

The major findings and contributions of the three selected studies of this dissertation are summarized in this section. In addition, major insights of the other research projects during the doctorate are briefly introduced and referred to. Overall, the dissertation started with a focus on finding an answer to the overarching research question as illustrated in Table 1 in the introductory chapter. It lies at the intersection between operations and supply chain management with information systems combining quantitative and qualitative approaches. The dissertation commences with an exploration of the topic resulting in a mixed-method literature review examining different use cases across all procurement domains, which helped to set the further research direction. Afterward, the two design science studies on the bundling problem and ethics for autonomous negotiation agents have been conducted based on information-processing theory and principal-agent theory contributing to the design science methodology in purchasing and supply chain management, which is still underrepresented today (Srai and Lorentz, 2019; Stange et al., 2022).

As shown in the review of the literature, many relevant applications are situated at the intraorganizational and interorganizational interface with marketing and sales functions. Procurement is thereby in a unique position to work with internal and external stakeholders in the supply network to profit from marketing insights from the internal organization, such as demand forecasting and requisitions planning but also from marketing insights from the supply market with essential industry and product information (Nitsche et al., 2021b; Wamba et al., 2021; Roy, 2022). Therefore, the studies zoomed on the purchasing-marketing interface, which holds significant potential for future research and practical applications (Nitsche et al., 2021a; Saenz et al., 2022).

5.1.1 Review of artificial intelligence and machine learning in procurement

Generally, purchasing organizations, suppliers and partners produce massive quantities of data. This large volume of data provides substantial potential for added value (Brinch, 2018), but this potential is often not yet fully exploited (Handfield et al., 2019; Allal-Chérif et al., 2021). There is thus a need to evaluate, structure, and provide insights on the increasing research and practical activities in the application of these emerging methods in procurement with industry case insights (Wamba et al., 2021). The state-of-the-art of artificial intelligence in purchasing and supply management is arguably in a nascent phase, for this inductive theory building has been proposed by Durach et al. (2021) as appropriate, which offers an approach for stepwise theory building that avoids the so-called miner approach, which consists of mere descriptions or enumerations.

The literature was therefore classified along the strategic, tactical, and operational dimensions of procurement tied with the Extended Purchasing Process and according to the Computing Classification System as an up to six-level ontology and de-facto standard developed by the Association of Computing Machinery. In total, 349 works at the intersection of information systems with operations and supply chain management were identified and reviewed. Thereof, 46 major works of artificial intelligence in purchasing and supply management meet the inclusion criteria that include a threshold of publication reputation and citations are described, compared, and assigned along these dimensions into eleven iteratively derived clusters summarized in Table 4.

The use case clusters in procurement were iteratively created, discarded, and rephrased by reading through the literature, and discussed among the coders by formulating useful headlines to find common denominators (Mayring, 2014; Thomé et al., 2016). The publications meeting the inclusion criteria are spanning 32 years from 1989 until 2020 exhibiting an increase over time as shown in Figure 6. The PRISMA statement in Figure 3 thereby provides a useful overview of the research methodology including the applied inclusion criteria of the systematic review of the literature. In addition, as shown in Figure 5, the major works identified in the review were mainly published in technical journals and conferences, only three of the 46 publications were published in a major journal with an emphasis on procurement, namely the Journal of Supply Chain Management. Thus, the work and this dissertation in general intend to encourage researchers to submit manuscripts to PSM-related journals to disseminate knowledge in this field and create a stronger basis of common terminologies and definitions.

As summarized in the coding scheme in Table 2, some works distinctly focus on concrete applications in particular of manufacturing, transportation, and construction but most works are rather general and not directed toward the particulars of specific uses cases or industries. The most often used technologies following the CCS classification are knowledge representation and reasoning, especially for dealing with uncertainty in supplier selection with so-called fuzzy algorithms as well as machine learning approaches with neural networks and distributed artificial intelligence. Future research can build on the iteratively identified use case clusters along the strategic, tactical, and operational levels of procurement highlighted in Figure 3. For instance, the four case studies of AI in PSM in Burger et al. (2023) may be assigned to the clusters ordering, supplier pre-qualification, risk monitoring, and cost analysis.

The technological adoption of artificial intelligence will not only have an impact on procurement operations, but also on the entire organization, external partners, and society, e.g., through regulations of the public procurement of these technologies, the usage of negotiation bots as well as demand planning, risk mitigation, and sustainability across the value chain (Deloitte, 2020; Spreitzenbarth et al., 2022b). However, the digital transformation is not an end but must provide value to the organization to justify the investment (Ziegler et al., 2019; Chui et al., 2022). Therefore, the technology must fit with the dynamic capabilities needs of the organization (Teece et al., 1997). It is important to note that the major works in this area mainly apply machine learning techniques while other methods have been seldom applied so far, i.e., planning and scheduling, search methodologies, theoretical foundations of AI, computer vision, and cross validation. The keywords and abstracts of the works meeting the inclusion criteria are visualized as a word cloud based on natural language processing in Figure 2.

In addition, twenty expert interviews have been conducted to empirically assess the clusters in terms of their business case and ease of implementation. In Figure 8, the use case clusters are mapped with the major works identified in the literature and the results of the expert interviews. The research activity from the material evaluation is matched with the results of the interviews normalized in standard deviations, where the mean is an aggregation of the use case attractiveness in terms of business value and ease of implementation as summarized in Table 3. Building upon this analysis the most attractive clusters are cost analysis and operational use cases regarding risk monitoring, ordering, and supplier evaluation as visualized in Figure 9. For instance, the German start-up Riskmethods has developed tools to anticipate purchasing risk that is gaining importance in response to the worldwide supply disruptions - such as during the COVID-19 crisis but also new regulatory requirements for supply chain transparency (The Federal Government, 2022).

Another cluster with a divergence in opinion was automated negotiation, which some experts rated as highly important and others as not so relevant as especially essential negotiations are not likely to be fully automated soon. Still, autonomous negotiation agents can support buyers in supplier selection with computing power, decision speed, and precision as described in Chapter 4. There is so much related research on computer negotiations that a separate cluster was created for it next to the cluster on supplier selection frameworks in general. In addition, the study of ethics for autonomous negotiation agents pertains to this highly relevant but also in academic and grey literature as well as the expert interviews controversially discussed use case for procurement organizations.

One of reoccurring themes in the interviews was that having both the domain knowledge and the technological toolbox will be an important skill set for future buyers. An often-mentioned pitfall in the interviews and literature was data generation with unequal probabilities of inclusion and opportunity structures. In addition, the talent gap might hinder the potential to be realized as well as legal and ethical aspects of artificial intelligence in procurement. While acknowledging the importance of training the existing workforce to facilitate the adoption of technology by buyers and stakeholders within and outside the organization, most interviewed experts concurred that the recruitment of new talent is imperative to effectively introduce and oversee these emerging technologies. Moreover, decision-makers often rely on their judgment known as algorithm aversion, i.e., rather believe in their calculations or gut feeling (Dietvorst et al., 2018) whereby the current developments of explainable AI may alleviate some of the current reservations (Balakrishnan et al., 2020).

Furthermore, for many of the interviewed experts, the main reasons for an investment in the technology are in particular strategic insights into the major supply markets and being perceived as an innovative business function. Others state that today many organizations are very problem-focused contrasting that technology champions are more pragmatic with a long-term perspective on direct and indirect savings, and a focus on data quality. Artificial intelligence technologies can thereby support procurement controlling and master data management such as eliminating duplicate supplier entries or correcting misspellings, classifying requisitions and invoices, or consolidating expenditures across individual group companies into the holding structure (SAP, 2020; Sammalkorpi and Teppala, 2022). As a result, these measures are expected to lead to substantial enhancements in data quality, thereby enabling the implementation of other use cases in operations and supply chain management.

A primary driver of implementation discussed in several interviews is the quality of decisions in combination with scalability. It is thus possible to review many contracts quickly and consistently providing negotiation support to the buyers. In addition, supplier sustainability was of the use cases with a strong difference in opinion in the assessment. Some experts rated the business value highly, others mainly in terms of marketing purposes. Due to relatively little previous research and the current general interest, artificial intelligence for supplier sustainability is an important area of further research. For example, the German automotive manufacturer Porsche introduced a sustainability rating and is using natural language understanding to screen media worldwide to identify potential violations of sustainability principles at an early stage (Gräve, 2021).

However, when establishing new solutions for instance for supplier pre-qualification, it is an important management challenge to properly align the organizational objectives and culture around procurement managers with psychological safety to actively use the available technology augmenting their skills and knowledge. This is essential in this example to motivate the entire organization in particular development, production, quality, and logistics to take the risk to qualify a new supplier without being penalized for not previously knowing this supplier in their commodity as their key area of competence. Furthermore, as pointed out by Loo and Santhiram (2018) and Li et al. (2023) among others, artificial intelligence has greatly impacted the procurement process with automation and AI-assisted sourcing decision-making. This aligns well with the idea of AI as a co-pilot for professional buyers that can augment their skills and expertise.

One of the first studies on artificial intelligence in procurement in a major PSM journal was recently published after this literature review has been conducted as Guida et al. (2023) in the Journal of Purchasing and Supply Management. The authors have analyzed the literature and conducted focus groups to better understand the benefits and challenges of AI adoption. In this paper, eight directions for further research have been proposed, i.e., spend analysis, risk management, supplier scouting, negotiation support, and fraud detection. While some of the results differ, key insights that are remarkably similar to this work such as the current early maturity stage and the focal areas for further research.

Moreover, the work explores the literature and offerings also from the perspective of technology providers and addresses one of the challenges encountered during the systematic review of the literature in the chapter in a slightly different way by adapting a process model by Spina (2008) of the strategic, tactical, and operational levels of procurement here called strategic purchasing, sourcing, and supply. As illustrated in the figure below, the mapping works well with the use case clusters identified in this review that were tied with the established

Extended Purchasing Process reference model by van Weele (2018) summarized in Figure 4. Yet, they were iteratively created, discarded, and rephrased in an open search by reading through the literature, and discussions among the coders by formulating useful headlines to find common denominators (Mayring, 2014; Thomé et al., 2016).

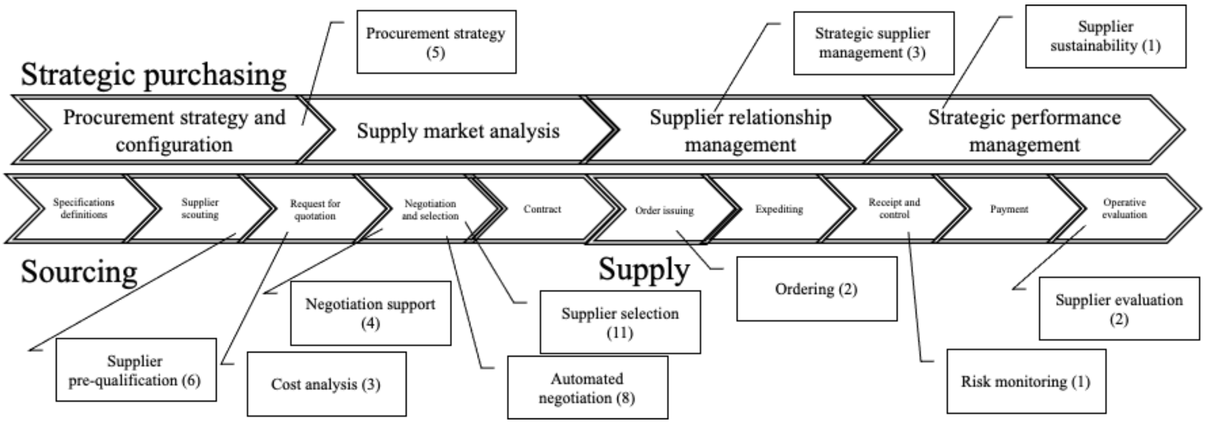

Figure 19: Mapping (own illustration extended by permission Guida et al., 2023)

As shown in the illustration in Figure 4 and the illustration above, comparatively much research has been carried out on the tactical level of procurement, especially on the negotiation and supplier selection stage where three use case clusters have been identified in the systematic literature search. Overall, the classification framework of the mixed-method review illustrated in Figure 7 combines commonly accepted models from supply chain management and computer science literature into a unified framework that enables a deeper understanding of artificial intelligence in supply management with clear boundaries. The results of the analysis of literature and expert interviews offer an overview of the state-of-the-art to spark new ideas and guide executives in the data-driven digital transformation to implement innovative applications in diverse settings. Also, the systematic review directed the subsequent steps in the doctoral research.

This work's methodological contribution is that the content analysis based on Mayring (2014) was extended by utilizing interviews to enrich the material evaluation to include a practitioner's point of view in the analysis of the literature. In addition, the Computing

Classification System provides a clearly defined ontology for the application of information systems (ACM, 2012). This is the first review in the field of OSCM to apply this framework and utilize the related Guide to Computing Literature by the Association of Computing Machinery to strengthen the interpretation and assessment of the coding, in particular what types of technologies have been applied. This work started with the umbrella term “AI” in mind, but for clarity in the discussion e.g., if an algorithm is artificial intelligence, machine learning, or another kind of computational method, it was decided to choose the de-facto standard from computer science as the various understandings were deemed confusing and not useful to conduct a structured review. Also, in the research outlook of this dissertation, a literature review based on the CCS classification and the complete spectrum of the SCOR model is proposed to conduct a systematic analysis of artificial intelligence in operations and supply chain management illustrated in Figure 20.

A relevant practical consideration is to align guiding purchasing principles, especially for public procurement of intelligent systems such as in Great Britain (Deloitte, 2020). Policies could be established to govern the design of these systems in a way that may benefit society and business partners, thus influencing the future development of artificial intelligence technologies and necessitating further research. Additionally, this inductive review highlights the significance of addressing ethical implications at the buyer-supplier interface, examining their impact on relationships, power dynamics, and profitability.

Finally, the results of the mixed-method literature review provide comprehensive answers to the three research questions. These findings contribute to the overarching research theme of the dissertation with a practically and theoretically relevant work that shows how artificial intelligence technologies can create value for procurement organizations.

5.1.2 Designing an AI decision support requisition bundler

Building upon those and the previous findings, another master thesis was set up at the University of Mannheim in the Data and Web Science Group to build a prototypical implementation of a bundling generator with an automotive case study organization designing an instantiation of an artifact to bundle purchasing requisitions in order to identify further saving potentials (Farida, 2022). As illustrated in Figure 10, the bundling generator receives sourcing planning information across the organization as input and provides prioritized options as output for bundling through natural language processing and supervised learning.

While well-researched, even minor improvements to the supplier selection process may save millions to the financial bottom line (Pal et al., 2013). For example, the tender design can be pre-configured through natural language understanding of the specifications, i.e., to optimize the bidder's list. This is applied, for instance in the Volkswagen Group, which deploys artificial intelligence to suggest to the buyer further possible suppliers (Hülsbömer, 2019). Due to the evolving nature, the design science research methodology is suitable for their analysis and optimization (Nitsche et al., 2021b) as a construction-orientated, problem-solving approach aiming at the creation and evaluation of useful information technology solutions for relevant organizational problems (Peffers et al., 2007). This objective is achieved through the development of innovative artifacts (Gregor and Hevner, 2013), in this case, a bundling generator to support the focal organization to drive down material and service costs.

Generally, the added value can be increased by bundling purchasing requisitions of commodities, internal functional units, and external suppliers. Prior research has indicated that bundling has the potential to yield additional savings exceeding ten percent (Schoenherr and Mabert, 2006). Typically, the bundling of requisitions throughout the organization is procedurally ensured by material group management also called commodity or category management, and it is considered one of starting points of formal procurement organization

(Monczka et al., 2020). Communication across various stakeholders in complex organizations is inherently slow and complex (Leeuwis and Aarts, 2011). As a result, the potential benefits of bundling may not be immediately evident and often only become apparent in later stages of the sourcing process, such as during supplier selection committees. By that time, it may be too late to achieve substantial cost savings through bundling (van Weele, 2018). This led to the goal of the case study to design an adaptable module that bundles purchasing requisitions in order to identify further saving potentials across direct and indirect procurement teams.

Based on a recent actual business setting in the automotive industry, several hundred purchasing requisitions from an ERP system were stripped of personal and confidential information, cleaned, and transformed into a structured data set with some missing data points. The data set includes textual information with free-text descriptions, numerical information with financial and temporal factors, and categorical information such as the approval status. A prototypical implementation has been designed in a three-step process along the three vectors projects, components or services, and suppliers as illustrated in Figure 10. An information system was developed that takes the sourcing planning from different formats across the organization as input and provides recommendations to bundle tenders continuously learning through feedback over time, e.g., through supervised learning.

Based on the input from the combined planning and historic data, different algorithms were applied to output actionable bundling recommendations to the buyers of the case study organizations that were assessed in terms of their quality and potential monetary savings. The specific setting of the focal organization with the main relevant information systems along with the respective time horizons and main users as well as the scope of the bundling analysis is shown in Figure 12. In addition, in Figure 13 the sourcing process has been mapped in collaboration with the case study organization and illustrates, how the bundling generator artifact has been embedded in the organization. Finally, a visualization with examples from Mini Batch K-means of the textual processing as bag of words is shown in Figure 14.

As practical advantages of the bundling generator for procurement organizations, not only could further cost reductions be achieved but also the sourcing planning process and its quality improved as better data input leads to better suggestions making the cost reduction potential transparent to management. These practical findings hold particular significance for solution providers of enterprise resource planning systems. By integrating a bundling model into requisition modules, these providers can offer a more robust decision-making foundation for configuring requests for quotation and facilitating negotiations across all their clients.

Furthermore, the bundling generator has the potential to function as a component within a broader AI module that complements the tendering system. For example, it can propose suitable bidders for a project, thereby contributing to enhanced process efficiencies. For large organizations, this might be initially surprising for the supply base to demonstrate the connectedness of the different business areas. In the realm of sales, key accounts play a crucial role in ensuring the quality of offers across the entire global sales organization (Wedel and Kannan, 2016). Similarly, lead buyers within the purchasing organization fulfill a similar function, making the bundling generator a valuable tool for their decision-making processes.

This empirical research builds upon the work conducted by Vlachos et al. (2016), which focused on developing a B2B recommender system to support marketers in a similar manner as the assistance provided to buyers in this study. More research on recommendation engines in the B2B context is needed in terms of exploring their potential applications as well as their effects on performance, success factors, and implementation hurdles. Being able to offer sales representatives a bundle of potential business opportunities, for instance, close to the end of the reporting period, could be a powerful tool to take advantage of the incentive structure of the counterparts of procurement, whereby the bundling generator can provide prioritized bundling opportunities whereupon the buyer can act upon.

The study makes three notable contributions to both literature and practice. First, it advances theoretical understanding by applying information processing theory to the bundling problem with an automotive case study. This is particularly relevant to the field of spend analysis, which has traditionally focused on retrospective analysis of purchasing orders and invoices to identify potential savings. This study breaks new ground by combining historical data with forward-looking procurement planning data, despite the inherent challenge that the latter practically be as information-rich and precise as data on past purchases. However, literature such as Qi and Luo (2020) or Russell and Norvig (2020) as well as this case study demonstrate that this challenge can be overcome. This finding is significant because it addresses the historical limitation of artificial intelligence techniques, which often required large amounts of data to build performative algorithms. This is encouraging for operations and supply chain management research, which often deals with limited information to solve relevant problems (Hazen et al., 2014; Gunasekaran et al., 2017). Overall, the study highlights the effectiveness of the Mini Batch K-means clustering algorithm, which was identified as the most performative model among the five assessed clustering algorithms. In addition, the study makes a valuable contribution to the fields of information processing theory and design science methodology, which are currently underrepresented in procurement and the broader domains of operations and supply chain management (Srai and Lorentz, 2019; Stange et al., 2022). By exploring these areas, the study helps to fill existing research gaps and advance the understanding and application of these theories and methodologies within the purchasing and supply management context.

Second, an artifact of the bundling generator has been created following Peffers et al. (2007) as illustrated in Figure 11. The derived design principles from the evaluation of the developed artifact as summarized in Table 7 are not only relevant for the case company but also for analytical tool providers, as it can expand sourcing and spend analytics solutions by incorporating forward-looking planning data into analytical frameworks. Technology providers can thus enhance their capabilities by enriching historical data, providing improved tool support for procurement organizations. In addition, procurement planning can be a strategic tool to proactively manage demand (van Weele, 2018; Planergy, 2022). In direct procurement, organizations typically have well-established cross-functional forecasting procedures in place. However, for indirect procurement, many organizations face challenges in obtaining high-quality data from their stakeholders. In this context, the bundling generator can serve as an additional incentive to encourage the use of procurement planning data. It can demonstrate the value to requesting departments, who act as internal customers of procurement, in terms of cost savings and improved planning security. For instance, by establishing long-term framework contracts with key suppliers, the generator can showcase the practical benefits of such collaborations.

And finally, third, the literature on bundling was reviewed from the perspective of the marketer and the buyer showcasing the potential to approach a common problem from other sides of the coin. While relevant solutions exist for purchasing and business-to-business marketing respectively, there is still research potential to provide better solutions for buyers and marketers to make use of the available data (Spreitzenbarth et al., 2022a) whereby AI-driven decision sciences can be essential to achieve higher value contributions (Gunasekaran et al., 2017; Li et al., 2023). Moreover, the evaluation of the requirements of the case study organization in Table 5 as well as the developed artifact led to the design principles in Table 7.

The discussion of the results of the case study provides an answer to the research question, of how to design an information system that supports buyers to identify further saving potentials by bundling requisitions. This contributes to the overarching research theme of the dissertation with a practically and theoretically relevant work that shows how artificial intelligence technologies can create value for procurement organizations. The code for the algorithmic models in the programming language Python, the anonymized dataset of the case study organization without proprietary or personal data, and the proposed clusters by the Mini Batch K-means algorithm along with their expert assessments will be made available upon qualified request.

5.1.3 Ethics for autonomous agents in business negotiations

Negotiations are an essential part of business, politics, and everyday life. Moreover, if done well negotiations can benefit all involved parties to better approximate Pareto-efficient agreements (Jennings et al., 2001). The insight of Moosmayer et al. (2013) as well as Spreitzenbarth and Stuckenschmidt (2021) that the results of a negotiation and in fact a tender, given its competitive situation and supply market are to a large degree predictable - combined with opportunities of artificial intelligence augmenting the skills of buyers such as in the bundling study in Chapter 3, makes autonomous negotiation an attractive use case for procurement organizations worldwide. Thus, there are upcoming start-ups such as Pactum in the United States of America or Botfriends in Germany as well as existing technology providers such as IBM that are working to build typically chatbot-based autonomous negotiation tools.

This is because typically there are not enough buyers to be able to touch all spending in the same way, which makes commodity buying and discretionary spend prone to be supported by artificial intelligence, whereby the buyers can provide oversight and parameter fine-tuning (Moosmayer et al., 2013). It is thereby essential to examine the ethical implications of utilizing artificial intelligence in the context of business-to-business negotiations at the purchasing-marketing interface of organizations in the public and private sectors. This pertains to how autonomous agents affect the power dynamics between buyers and suppliers including deception, hard-bargaining, and other negotiation tactics. For example, one common design approach of artificial intelligence is to automatically learn models by observing human behavior. Facebook has used this approach to train autonomous negotiators with the unintended consequence was the agents learned to lie (Gratch, 2021).

Autonomous negotiation can support the buyers in the supplier selection with computing power, decision speed and precision. Human buyers are confronted with the dilemma of deciding where to prioritize their efforts in order to enhance outcomes across various dimensions, including time, budget, and quality. As a result, many smaller requisitions are often inadequately negotiated (Monczka et al., 2020). Technological tools such as catalogue management systems like Amazon Business or GEP Smart for spot buying of minor goods (Spreitzenbarth et al., 2022b) have been developed to ease this issue - as well as a myriad of negotiation procedures to ensure the supply of the organization's essential, high-value goods and services. In addition, previous research such as by Saenz et al. (2020), Cui et al. (2022a), and Burger et al. (2023) has explored the performance of artificial intelligence agents in comparison to human agents, indicating that hybrid human-AI teams at least currently outperform humans or AI alone.

Artificial intelligence opens the potential toolbox for buyers and marketers alike as summarized in Table 8 illustrating that ethical considerations at the buyer-supplier interface are not a new challenge. Buyers and suppliers may choose to deploy artificial intelligence agents to handle small requisitions and utilize human-AI teams to maximize performance. Yet, this may leave many especially smaller suppliers behind as the digital divide might widen. Vice-versa, what if the supplier has superior negotiation technology? There is a stream of research that can be drawn upon on optimizing negotiation situations between humans that often involved ethical dilemmas for both sides, for instance, how much information should be shared within the supply network (Baarslag et al., 2017, Gratch, 2021). Moreover, especially for the long tail of external spend that traditionally has not been able to be negotiated by human agents other than by catalogue providers as emphasized by the column for no negotiations in Table 8, a business model such as sharing the achieved cost savings could align the interests the buying organization with the negotiation technology provider next to traditional costs per transaction or flat fee based on the covered spend.

The automotive industry has been severely criticized for hard bargaining tactics, for instance, the former chief procurement officer José López with General Motors and later Volkswagen (Rose, 2016). This can lead to severe distortions of buyer-supplier relationships, e.g., in the aftermath of the emissions offense, Volkswagen had to halt the production of several plants due to a dispute with two suppliers connected with the industrial consortium Prevent Group (Rogers and Fell, 2017). Human negotiators often have a preferred set of negotiation strategies that can be viewed from different angles, for instance by the underlying mindset of "you lose, I win" to a win-win mindset as advocated by the method of principled negotiation developed by the academic consortium Program on Negotiation (Fisher and Ury, 1981).

Current operations and supply chain management research have largely overlooked ethical lenses, as emphasized by Quarshie et al. (2016). Most studies on procurement ethics have been conducted years ago and there is a need to conduct further research given the recent developments in digitalization and sustainability (Chen, 2023). To illustrate one of the most discussed ethical issues in autonomous negotiation literature, suppose an "ethical knob" that buyers and marketers could adjust to guide the decision-making processes of the artificial intelligence agents such as shown in Figure 18. The behavior of the autonomous negotiation agents could be adjusted according to the ethical attitudes of the organization's leadership and general culture. An analogy can be drawn to how human buyers are embedded within the organization's norms, beliefs, and general perceptions of what is appropriate behavior - and generally reflect this internal culture in the exchange with external partners, such as suppliers on a spectrum of altruistic to egoistic. Hence, in some organizations, negotiation tactics such as hard bargaining, withholding information, lying, or emotional manipulation but also others such as intentionally leaking wrong information are either considered as appropriate or not (Rogers and Fells, 2017).

In the systematic review of the literature in Chapter 2, no academic study was identified focusing on ethical considerations of the application of artificial intelligence in procurement. In addition, the application of AI in business negotiations was one of the use cases where the expert assessment differed strongly making it a relevant area for further investigation. Ethics for artificial intelligence in procurement is still in a nascent stage with manifold opportunities for future research, e.g., how to balance sustainability and financial aspects in supplier selection frameworks in decision support systems based on artificial intelligence. Yet, for instance, Great Britain has already published guidelines for the regulation of artificial intelligence technologies in public procurement highlighting the benefits but also the need for control (Deloitte, 2020). Procedures such as those by the international organization World Economic Forum (2019) advocate the possibility of procurement to effectively act as a gatekeeper in particular by setting privacy and information security standards and making ethical considerations part of the offer evaluation criteria.

As AI will become more readily available, ethical considerations especially at the buyer-supplier interface are essential for their acceptance and buyer-supplier relationships (Nitsche et al., 2021a). This study makes valuable contributions to both academic literature and practical applications in three distinct areas. Firstly, it contributes to the field of design science methodology and the ethical considerations surrounding artificial intelligence. Secondly, it extends the understanding of principal-agent theory by examining the implications of autonomous agents in relation to existing outsourcing literature. Thirdly, it provides a practical and useful ethical design framework for the development and implementation of autonomous negotiation agents, benefiting technology providers, as well as procurement and marketing organizations across various sectors on a global scale.

The first contribution of the study is to the design science methodology and ethics for artificial intelligence in operations and supply chain management. Other scholars can build upon this work in similar ethical frameworks for the application of autonomous agents in business settings. Following Walsh (2011) it is crucial to provide essential details and justifications for the experiment, including its purpose and the perspectives considered, along with their respective reasons. Thereby, the work considers non-Western perspectives, i.e., role ethics in the thought experiment whereas in autonomous agent research, predominately consequentialist and deontological ethics are employed. In addition, the work links major schools of thought of normative ethics to the negotiation literature through the design science methodology with the meta requirements and design principles that are summarized in Table 10. Also, the thought experiment aims to find answers summarized in Table 11 to key inquiries regarding autonomous negotiation agents using the five normative ethical approaches. Furthermore, thought experiments are methodologically a widely used type of experiment especially in applied ethics (Brendel, 2004), however, thought experiments have seldom been applied in operations and supply management (Spina et al., 2016; Tate et al, 2022). Thereby, this work takes part in the discussion of automation versus augmentation (Raisch and Krakowski, 2021), on the one hand by theorizing when and how to deploy autonomous agents in business negotiations with the conceptual model in Figure 16 and on the other hand by initiating an academic discourse over ethics for autonomous negotiation agents.

The second contribution of this study is the recognition of the intersection between autonomous agents and the outsourcing literature. It sheds light on the unique characteristics of the agency of autonomous agents in business-to-business settings, distinguishing it from the more established usage in the business-to-consumer environment (Gratch, 2021). No previous study has been identified in the literature review that explicitly explores the relationship between autonomous agents and the outsourcing literature in this context. Hence, more research should be conducted to understand, which concepts of the outsourcing literature such as Ndubisi and Nygaard (2018) and Pournader et al. (2019) may be transferable under which circumstances to the emerging literature on autonomous agents.

Finally, the third contribution of the study is the derived ethical design framework illustrated in Table 10 can be practically useful not only for negotiation technology providers but also for procurement and marketing organizations considering applying autonomous negotiation agents. This pertains in particular to the ten design principles for their successful development and user adoption based on the discussion of the related literature and the conducted thought experiment.

To sum up, the technological adoption of autonomous negotiation agents is still in the early phase. Innovative organizations like Walmart, Volkswagen, Siemens, Maersk, and Facebook have already begun exploring and implementing autonomous negotiation agents, providing valuable insights for the ongoing progress of this technology. Solution providers are actively working towards enabling the adoption of autonomous negotiation agents in the industrial marketing and procurement domains. As negotiations play a crucial role in buyer-supplier communication, the emergence of these agents is expected to have a significant impact on various aspects of buyer-supplier relationships.

Considering the potential implications, it becomes imperative to establish ethical guidelines, regulations, and design principles governing the behavior and interactions of these agents. The ethical design framework in Table 10 as well as the discussion of the related literature and the thought experiment provides an answer to the research question, of what are the major ethical implications of autonomous negotiation agents at the buyer-supplier interface and how could they be addressed. This study thereby contributes to the overarching research theme of the dissertation with a practically and theoretically relevant work that shows how artificial intelligence technologies can create value for procurement organizations.

5.2 Limitations

As with every study, several important limitations are relevant to this dissertation. This pertains in particular that overall, the adoption of artificial intelligence in purchasing and supply management is still in its early stage. In addition, as shown by previous research and grey literature such as the state of artificial intelligence surveys (Chui et al., 2022; Mittal et al., 2022), in general, procurement is not yet on the same level as other business functions in the digital transformation toward Industry 4.0 (Batran et al., 2017; Bienhaus and Haddud, 2018). This is especially important when comparing its technological maturity with the counterparts in business-to-business marketing and sales functions (Handfield et al., 2019).

Moreover, as summarized in Table 1, during the doctorate, several theories, research methods, use cases, and technologies have been applied to find an answer to the research question, of what value artificial intelligence can provide for procurement organizations. It could have arguably less effort to concentrate on a certain theory, method, technology, or application. Still, for instance, the bundling study and ethics for autonomous negotiation agents are both based on the design science methodology. Notably, most works meeting the inclusion criteria of the literature review in Chapter 2 do not explicitly mention applied theories, yet some works are theoretically based on fuzzy logic, transaction cost economics, and game theory. In addition, the organizational setting for most of the identified research is on larger organizations. Although case studies, experiments, and frameworks like design principles may not form a complete theory, they play a crucial role in the process of theorizing and can contribute to the development of new theoretical insights (Eisenhardt, 1989; Gregor and Hevner, 2013). Still, overall, though the diversity in theory, method, technology, and application individual insights are sought to answer the research question that are synthesized in this thesis by combining quantitative and qualitative research approaches.

Several investigated use cases in this doctoral research lay at the purchasing-marketing interface, for instance, the inductive literature review in Chapter 2 surveyed several boundary-spanning use cases such as automated negotiation, risk management, and supplier evaluation highlighting their interconnectedness. In addition, the bundling generator in Chapter 3 takes a concept that has already been applied in the B2B marketing context at IBM by Vlachos et al. (2016) to the purchasing side. Also, the design science study on ethics for autonomous negotiation agents in Chapter 4 explores a critical aspect of future buyer-supplier communication and relationships. However, due to the necessary focus of the analysis, available data, and practical interest, all studies have been conducted from the perspective of the buying organization. Future research on artificial intelligence in purchasing and supply management could focus on the perspective of the suppliers - following the general call for more research from the supply side as outlined in the recent editorial of the Journal of Purchasing and Supply Management as an opportunity for business-not-as-usual research in procurement (Knight et al., 2022).

Regarding the digital transformation and artificial intelligence technologies in particular, further research should be conducted from the perspective of information technology providers such as Guida et al. (2023). In addition, it would be interesting to consider the diverse views such as from the requestors of buying organizations as well as other external stakeholders such as auditors and regulatory agencies. For instance, the study Spreitzenbarth et al. (2022a) has explored the technological adoption of artificial intelligence in purchasing and B2B marketing - and the second and third studies of this dissertation provide useful insights to technology providers in particular for spend analysis and autonomous negotiation solutions.

Moreover, as a dissertation in collaboration with a private and large organization in the automotive industry in Germany - while this is true for single-organization case studies, and although measures were taken to ensure that the findings are applicable in the broadest set possible in terms of organizational type, size, industry, location, and culture - there is necessarily a focus on the specifics of the organizational and industry characteristics. This pertains to the types of data that have been collected and processed within their organizational environment and core objectives. In addition, as pointed out in the literature review in Chapter 2, also outside of the realm of procurement, not much research has yet focused on how small and medium-sized enterprises can benefit from the potential value of artificial intelligence. This may be because AI requires skills, training, and costs for maintenance. However, as the technology is becoming more readily available through emerging startups and current technology providers that are expanding their tools with AI capabilities, it becomes more accessible for instance through plug-and-play software as a service offerings, and thus providing a chance especially for small and midsize businesses not to fall behind in the digital divide (Nitsche et al., 2021a; Saenz et al., 2022).

As pointed out by Li et al. (2023), artificial intelligence could potentially widen the gap between emerging and developed markets. Generally, in Germany and Central Europe, the usage of AI is gradually coming from research into application as it is pointed out in the overall theme of this dissertation. There is thus much related general interest in relevant research and practical solutions by information technology providers across all areas of industry, government, and society - which has spiked through the introduction of ChatGPT to the public (Alba, 2022). Moreover, there are several national and transnational strategic initiatives such as European Commission (2022) to promote the technology, but also efforts to regulate and avoid potential harm. The automotive industry is a key industrial sector in Germany and other countries across the world. The dissertation is thus an example of an essential industry that can use emerging technologies to advance processes, but also their products in particular in regard to autonomous driving and safety (Dremel et al., 2017; Hofmann et al., 2017; Klee et al., 2023).

Conducting qualitative and quantitative research at the intersection between disciplines such as information technology with operations and supply chain management can be challenging, as the disciplines are often characterized by the preferred methods, theories, shared ways to view problems, wording, background knowledge, and research interests (Tate et al., 2022). For the literature review as the first study of the dissertation, there are a myriad of different angles that may be relevant for executives in modern procurement organizations looking for guidance in their digital transformation journey such as set forth in the Volkswagen Procurement Strategy 2030 that not all potential questions can be answered in one study. In addition, it could have been less work to straight forward assign the identified major works of artificial intelligence in purchasing and supply management to an established framework such as the Extended Purchasing Process instead of conducting a search for common themes loosely tied to it as conducted retrospectively in Figure 19 based on the reference process model in Spina (2008) that has been adapted in Guida et al. (2023).

However, the identified use case clusters that emerged from the review of literature have been useful to prioritize and anchor the subsequent research projects in the doctoral research - and are hopefully equally helpful to other researchers as indicated by the citations of the early version as International Purchasing and Supply Education and Research Association conference paper. Although the systematic review of the literature in Chapter 2 is quite comprehensive, due to the necessary focus, for instance, maturity models, the necessary skill set of future buyers, or a detailed analysis of enablers, technology diffusion processes with success factors, and general roadblocks such as concerns about cyber security, data protection, data privacy as well as algorithms fairness are left for future elaboration and at least to some degree have already been examined in encompassing literature streams at the intersection between operations and supply chain management with information systems.

Secondly, the bundling generator study based on information processing theory could be extended with an action intervention, which might lead to further theoretical contributions to the fields of bundling, spend analysis, commodity management, strategic procurement planning, and requirement management. In addition, considering the perspective of the supplier base, for instance through interviews or surveys might be an interesting extension of the study. An alternative approach would be to enhance the case study methodology by combining the design science approach and information processing theory with a simulation that captures bundling effects. Additionally, the developed models can be implemented in various organizational environments, leading to a comprehensive multiple case study research.

This approach could enable the comparison of results in terms of model accuracy, as well as the evaluation of the impact on both quantitative and qualitative performance indicators, such as cost savings, buyer perception, stakeholder satisfaction, and the effort required for data exploration, model refinement, and process adjustments. Furthermore, while the selection of the five clustering algorithms was based on the review of the literature and the specific requirements identified in collaboration with the case study organization as summarized in Table 5, future research could explore other supervised clustering algorithms for evaluation. Another way to improve the results is by leveraging unsupervised learning techniques using the labeled data available from expert buyers' assessments in the case study.

Similar to the business-to-business recommendation engine employed by IBM for key account managers in Vlachos et al. (2016), incorporating a textual interpretation to explain the rationale behind the created clusters can further enhance their accountability. By utilizing this artifact, not only can additional historical and planning information be utilized, but the quality of input can also be improved, particularly in terms of the supplier dimension, leading to further enhancements in the models. Moreover, while informal exchanges with leading tool providers were found valuable for setting up and implementing the study, conducting formal interviews using a semi-structured protocol could offer additional insights. Additionally, as illustrated in Figure 12, gathering information from the supply base regarding capabilities and capacities can provide crucial insights for long-term organizational planning processes. This aspect becomes particularly relevant in light of recent events such as the semiconductor crisis, which has significantly impacted the automotive and other sectors of the economy (Schuh et al., 2022).

Finally, for the third study, while with pragmatic, utilitarian, virtue, role, and deontological five main philosophical schools of thought were taken into consideration in the analysis based on principal-agent theory, other important schools such as Islamic philosophy or the Ubuntu philosophy of personhood and interpersonal relationships may have contributed further to the study. Still, this work considers non-Western perspectives, i.e., role ethics in the thought experiment whereas in autonomous agent research in general, especially consequentialist and deontological ethics are employed (Bench-Capon, 2020; Wilburn, 2022). Moreover, to further strengthen the research methodology, the results of the design science approach based on the review of the literature and the thought experiment could be triangulated with a case study based on the ethical design framework or by evaluating existing solutions of autonomous negotiation technology against the design artifact.

In addition, the intersection between autonomous agents and the outsourcing literature can be analyzed in more detail in future research since their connection did only become apparent to the researcher during the analysis, of why and how the agency of autonomous agents in business-to-business settings is different from the already more established usage in the business-to-consumer environment visualized in Figure 18. Also, more research is needed, on what characteristics fundamentally differentiate human and AI-based agents in business negotiations. At least during the review of the literature for this work, no study was identified that has linked these two research streams yet, from a principal-agent perspective, autonomous agents play a similar role as the outsourcing agency. Although informal exchanges with technology providers were conducted during the study, formal interviews with solution providers, subject matter experts, regulators, buyers and marketers and their internal as well as external stakeholders may provide further insights. In particular, considering the external perspective for instance through expert interviews or a survey could be an interesting extension of the study.

The effects of introducing autonomous negotiation platforms such as by Pactum on established providers for electronic negotiation auctions and catalogue management systems should be explored in future research as visualized in Figure 16, for instance through case studies of early adopters. Moreover, further research may be conducted, on how an autonomous negotiation platform can be integrated into the overall information systems landscape of buyers and marketers alike, in particular enterprise resource planning, electronic sourcing, and customer relationship management systems. Also, ethical guidelines must provide value to the principal organization. If one bot is strongly restrained in its possible behavior, and could not detect destructive negotiation tactics by the opposing party, no self-interested party would use such a bot. Nonetheless, just like in buyer-supplier relationships in general, it is important to consider ethical principles in the conduct of business everybody bots offer the potential to make data-driven decisions without inherent biases unless they are implicitly included in the dataset.

To sum up, this dissertation aims to contribute with a comprehensive groundwork whereupon future research can be built upon focusing on specific characteristics of artificial intelligence technologies for concrete use cases in procurement such as cost analysis, negotiation support, or supplier sustainability – or their ethical implications, or regulation in particular for the public procurement of these emerging technologies, or their effects on organizational performance, or their impact on buyer-supplier relationships, and many different angles subsequent research may illuminate.

5.3 Research outlook

Overall, the field of artificial intelligence in purchasing and supply management is still in a nascent phase with many opportunities for future research and innovative applications as pointed out in the review of the literature in Chapter 2. So, if you are asking yourself now how to start, Andrew Ng, who is one of the most recognized thought leaders in artificial intelligence has given managerial decision-makers the following advice: *"Tapping the power of AI technologies requires customizing them to your business context. The purpose of your first 1-2 pilot projects is only partly to create value; more importantly, the success of these projects will help convince stakeholders to invest in building up your company's AI capabilities. When you're considering a pilot AI project, ask yourself the following questions: Does the project give you a quick win? Is the project either too trivial or too unwieldy in size? Is your project specific to your industry? Are you accelerating your pilot project with credible partners? Is your project creating value?"* (Ng, 2019).

Generally, the technological adoption of digital technologies can be approached from the consideration of the feasibility or technical difficulty, and the use case or value to the business (Ziegler et al., 2019) as shown in the evaluation of the expert interviews in Table 3. Overall, the experts expressed a preference for prioritizing business value over the ease of implementation. For each of the identified use case clusters of the literature review on artificial intelligence in procurement, a dissertation could be set up in future research to focus specifically on a specific area in procurement management processes. Next to replication studies, meta-studies on the identified use case clusters and concrete practical applications in case studies and action design research, the following questions were derived through discussions among the research team of the review of the literature in a brainstorming session as future research direction to develop new theory:

- What is the impact of artificial intelligence applications on business performance in purchasing and supply management? During the literature review, no study was identified that focused on the impact on actual performance, which is likely due to the still nascent stage of research and applications but could be significant to drive technological adoption. This may build upon research on the impact of procurement 4.0 on performance like Bienhaus and Haddud (2018)
- How does procurement compare in the technology adoption with other functional areas, i.e., the negotiation partners in sales and marketing functions, and why? This could be built upon the propositions developed in the explorative research study Spreitzenbarth et al. (2022a). In addition, cross-functional use cases have been highlighted throughout this work considering the unique position of procurement in the supply chain network (Nitsche et al., 2021b; Wamba et al., 2021; Roy, 2022)
- How can supply chain integration further be supported by artificial intelligence? This aspect builds on the previous point that information sharing within the network could yield large cross-functional savings for the organization, for instance through better demand planning leading to inventory cost reductions and lead time improvements
- Which ethical aspects should be considered for artificial intelligence in procurement? No study was identified in the review of the literature that focuses on ethical aspects of the application of artificial intelligence, for instance, for autonomous negotiations with severe implications for buyer-supplier relationships as outlined in Chapter 4
- Which regulations should be introduced regarding procuring artificial intelligence technologies and in terms of applications in procurement organizations? The literature, in particular practitioner reports, has focused on regulations of buying and applying

artificial intelligence technologies in the domain of public procurement. However, this is also relevant in other organizational settings, especially for larger private enterprises

Next to these five highlighted potential research questions, the following three topics could be relevant for future research and practice. Firstly, a literature review can be conducted based on the Computing Classification System for the six supply chain management processes of the SCOR framework or alternatively other established frameworks such as the supply chain task model by ten Hompel and Hellingrath (2007). This may build upon the literature review in Chapter 2 as well as the work by Min (2010) and Brintrup (2021) among others reviewing relevant research and field applications along the supply chain by taking the CCS as clearly defined ontology from computer science literature for precision in terminology and as demarcation guideline as illustrated in the figure below.

Classification framework		SCOR model						Other
		Plan	Source	Make	Deliver	Return	Enable	
CCS model	Artificial intelligence and machine learning technologies		[Strategic, tactical and operational] Spreitzenbarth et al., 2022b [Solution provider] Allal-Chérif et al., 2021 Guida et al., 2021 [Models and case studies] Cui et al., 2022a Cavalcante et al., 2019 Schulze-Horn et al., 2020	For instance Li et al., 2017	For instance Woschank et al., 2020			
		For instance Min, 2010 or Brintrup, 2021						
	Big data analytics	For instance Gunasekaran et al., 2017, Nguyen et al., 2017, or Choi et al., 2018a						
Other								

Figure 20: Framework for the suggested encompassing literature review

Secondly, the literature review has shown that the main research methods are case studies, followed by model building, and simulation such as the procurement workflow optimization in Spreitzenbarth et al. (2021). However, no replication study was identified indicating a gap in theory-building work in this evolving field. In addition, no study was found that focuses on ethical questions or their impact on organizational performance. For example, future research might employ the action design research methodology empirically applying artificial intelligence in the procurement function, e.g., building on the bundling generator study in Chapter 3 or other relevant use cases discussed in the review of the literature in diverse organizational settings. Generally, action design research is still underrepresented in procurement research (Spina et al., 2016; Tate et al, 2022). This constitutes a research opportunity with the possibility of providing practical value to procurement organizations. Also, as pointed out in the previous section on the limitations of this dissertation, more research at the intersection between operations and supply chain management with information systems should be conducted from the perspective of the suppliers and the technology providers. Buyers are encountering suppliers that operate at varying degrees of digitalization with increasing frequency (Burger et al., 2023). This shift in technological support may leave in particular smaller suppliers behind as the digital divide might widen between buyers and suppliers (Nitsche et al., 2021a). More such research is needed to better understand, how buyers and suppliers can cope with such challenges.

Thirdly, as the review of the literature in Chapter 2 has shown that there is a gap in examining the ethical implications of artificial intelligence. Following the example of ethics for autonomous negotiation agents in Chapter 4, more essential purchasing and supply management processes can be considered in future research for instance, how to balance sustainability and financial aspects in supplier selection framework in decision support systems based on artificial intelligence. In addition, ethical guide rails are needed for purchasing advanced technologies based on artificial intelligence, i.e., in public procurement. For instance, Great Britain has published guidelines for the regulation of artificial intelligence technologies in public procurement highlighting the benefits but also the need for control (Deloitte, 2020). Manifestos such as those by the World Economic Forum (2019) advocate the potential of procurement to effectively act as a gatekeeper in particular by setting privacy and information security standards and making ethical considerations part of the offer evaluation criteria.

The consideration of ethical questions is important for the technological adoption, which is likely to significantly change buyer-supplier communication and relationships (Nitsche et al., 2021a). Leveraging the potential of artificial intelligence, especially in the interaction with external partners could become a significant power factor in the future. Thus, as concluded throughout this thesis, it is paramount to create a consistent technology strategy, lay the data foundation, attract and develop the talent now to profit in the future - when chief procurement officers may get asked the question, as pointed out by Klee et al. (2023) of how they managed to become the analytical powerhouse within the organization.

Dynamic capabilities theory has provided a solid foundation for developing relevant research projects at the intersection between operations and supply chain management with information systems in the digital transformation toward the vision of procurement 4.0 as outlined in the Volkswagen Procurement Strategy 2030. The overarching research question of how artificial intelligence can bring value to purchasing and supply management does not have a singular answer. However, this dissertation effectively demonstrates, summarizes, and emphasizes the wide range of opportunities for future research and practical applications in this field. As an example, in the third study of the dissertation, a controversial aspect of machine ethics for procurement with autonomous negotiation agents was researched highlighting not only the potential value the technology can provide but also on one of its main challenges.

The general outlook of the conducted research on the discussion of augmentation versus automation through artificial intelligence in management (Raisch and Krakowski, 2021) is largely optimistic that current state-of-the-art as well as successive advances can provide value for procurement organizations by augmenting the skills of buyers but also automate process steps to enable the buyers to concentrate on value-adding tasks. Considering decision-making echelon models such as Boute and Van Miegham (2021), the expert interviews in Chapter 2 have shown that some organizations only want artificial intelligence to support human decision-making for instance through recommendation systems that augment the skills of buyers as in the bundling study in Chapter 3, others are open to AI-based systems such as autonomous negotiation agents in Chapter 4 that can take their own decision whereby humans focus on parameter tuning and oversight (Moosmayer et al., 2013).

While artificial intelligence techniques will certainly contribute to the further automation of purchasing activities as previous digital technologies, no evidence was found during the doctoral research that there will be no people working in the procurement function of the future, for instance, not all types of negotiations are prone to be carried out by autonomous agents. Moreover, as discussed in the literature review and the autonomous negotiation study, these agents need to be set up with parameter tuning that can only be derived by in-depth discussions with the relevant stakeholders to align the negotiation criteria with the overall organization's priorities. Moreover, throughout the dissertation, information flows and business processes are examined that are typically embedded in the information systems landscape of an organization. These are in particular relevant for enterprise resource planning, electronic sourcing and negotiation auctions, catalogues, supplier relationship and customer relationship management. More research is needed on how first these existing systems can be expanded with AI-based technologies, and second how new types of information systems will be integrated into the overall systems landscape such as platforms for autonomous negotiations.

A recent survey conducted by the University of Mannheim in partnership with the Institute of Supply Management showed that data quality emerged as the primary performance obstacle in procurement organizations. Data quality issues were closely followed by challenges such as a shortage of qualified employees, budgetary constraints, and limited data availability (Bode et al., 2022). All four roadblocks of the survey are directly relevant to the technological adoption of artificial intelligence in procurement as any information technology needs high-quality data to provide value as well as qualified employees and an investment in technology, training, and maintenance in order to gain from it. Hence, procurement executives need to ask the right questions today to lay a solid foundation of data, talent, and guidelines to profit in the future as the technology matures and becomes more readily available.

Human-AI collaboration is highlighted in the bundling generator study that provides procurement teams with important insights to create, prioritize, and obtain value in collaboration with other internal and external functions. Also, the study on autonomous negotiation agents emphasizes the potential performance improvements of hybrid human-AI teams in business negotiation building on research such as Cui et al. (2022a) and generally hybrid intelligence by Saenz et al. (2020) and Burger et al. (2023). Furthermore, once a higher level of maturity of artificial intelligence in purchasing and supply management has been reached, it would be interesting to carry out a literature review based a text analysis approach. This could be conducted based on the use case clusters developed as common themes during the coding in the literature review in Chapter 2. Finally, the doctoral research described in this dissertation on artificial intelligence technologies in purchasing and supply management ultimately may contribute towards procurement becoming one of the analytical powerhouses of the organization that it potentially can become.

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Appendices

A. Semi-structured expert interview guideline

A.1 Background understanding

- Could you briefly describe your organization, e.g., headquarter, history, number of employees, products, revenue, procurement volume, etc.?
- What is your current position? How many years have you been in this position?
- What is your understanding of artificial intelligence?
- Have you had experience with artificial intelligence methods at your work? If yes, what kind?
- When you implemented AI technology, what was the influence of processes and results? What is your main motivation for this investment (efficiency/ quality/ costs)?
- What kinds of structured and unstructured data do you often process and analyze? Where does the data come from? Besides, which decisions must you take based on this data?
- What kind of information system are you currently using such as enterprise resource planning tools?
- Where would you rate your current analytics capability and why?
- Are you likely to adopt robotic process automation or AI methods within the next two, five, or ten years?
- What do you think AI champions such as Amazon, Alibaba, or Google do differently?

A.2 Evaluation of use case clusters

In the literature, several clusters were identified and iteratively categorized following a search for common themes in the literature loosely tied with established frameworks such as the Extended Purchasing Process (van Weele, 2018). Please rank them on their business value and ease of implementation from one denoting very low/ hard to five denoting very high/ easy.

See Table 3 in the section on expert interviews.

Business value:

- Financial value considers the savings and sales growth potentials
- Customer value targets service quality, product quality, and process improvements
- Strategic value views sustainability, degree of innovation, and differentiation

Ease of implementation:

- Input data considers data quality, availability, and complexity of the data sources
- Required know-how assesses the required domain and technical knowledge
- Change effort considers process changes, system adaptations, and culture

Use case cluster:

- Procurement strategy sets the strategic orientation of procurement
- Strategic supplier management concerns the overall supplier portfolio and procurement spend
- Sustainability considers environmental aspects
- Supplier pre-qualification determines the potential suppliers
- Cost analysis dives deep into the costs to identify saving potentials
- Negotiation support is the preparation and assistance of buyers
- Automated negotiation means machine-based negotiation

- Supplier selection determines the framework to select the right suppliers
- Risk monitoring identifies risks along the process
- Ordering considers the workflow to complete the order
- Supplier evaluation monitors the performance of selected suppliers

A.3 Closing questions

- At which level of procurement (strategic, tactical, and operational) is AI likely adopted the quickest?
- Which of the use cases would you rank #1, #2, and #3? These will be marked above with a bold script
- Which other interesting use cases could you see? They can be added accordingly in Table 3

B. List expert interviews mixed-method literature review

Table 12: Anonymized list of expert interviewees

Organization type	Country	Employees	Position	Order
Manufacturer	Germany	1,000 - 50,000	Procurement Analytics Manager	I
Consultancy	Germany	1,000 - 50,000	Senior AI consultant	II
Manufacturer	Germany	1,000 - 50,000	Analytics Procurement Specialist	III
Information technology	Germany	< 1,000	Co-Founder	IV
Retail	Germany	> 50,000	Supply Chain Director	V
Research institute	Netherlands	1,000 - 50,000	Professor of Supply Management	VI
Information technology	United States of America	> 50,000	Lead Architect Connected Customer	VII
Information technology	Germany	< 1,000	Co-Founder	VIII
Research institute	Germany	1,000 - 50,000	Senior Researcher	IX
Manufacturer	Germany	1,000 - 50,000	Vice President Procurement Strategy	X
Information technology	Germany	> 50,000	Senior Procurement Product Manager	XI
Consultancy	United States of America	1,000 - 50,000	Partner and Director	XII
Manufacturer	Germany	> 50,000	Digitalization Procurement Manager	XIII
Information technology	United States of America	> 50,000	Director Purchasing Information Technology	XIV

Information technology	China	> 50,000	Senior Business Development Manager	XV
Consultancy	Germany	< 1,000	Associate Partner Purchasing Innovation	XVI
Consultancy	United States of America	> 50,000	Principal Director	XVII
Telecommunication	Great Britain	> 50,000	Director Supply Chain Management	XVIII
Manufacturer	Germany	1,000 - 50,000	AI Innovation Manager	XIX
Manufacturer	Germany	1,000 - 50,000	Managing Director Evangelist Data Science	XX

C. Bundling purchasing requisitions Mini Batch K-means examples

Table 13: Clusters with expert judgment Mini Batch K-means examples

Line item	**Creation**	**Value**	**ECLASS**	**Cluster**	**Expert judgment**	**Potential saving**
29	09.07.2021	4,040,000	Development service	80	High confidence	182,287
28	09.07.2021	1,327,940	Development service			
62	23.07.2021	708,307	Development service			
560	02.07.2021	7,005	Software	16	Medium confidence	44,441
558	02.07.2021	6,660	Software			
384	10.06.2021	7,298	Enterprise (IT, service)			
26	08.07.2021	52,320	Software			
484	23.06.2021	7,130	Service			
595	09.07.2021	6,736	Software			
592	09.07.2021	24,517	Software			
85	29.07.2021	438,240	Service			
170	29.07.2021	198,862	Electric, electronic component development (motor vehicle)			
729	30.07.2021	438,648	Software			
487	23.06.2021	8,800	Service			
610	13.07.2021	52,110	Software			
369	03.06.2021	8,780	Enterprise (IT, service)			
574	07.07.2021	150	Food, beverage, tabacco	7	Low confidence	12,945
697	21.07.2021	1,878	Antenna system			

457	21.06.2021	72,039	Development service			
576	07.07.2021	2,398	Transformer Station			
456	21.06.2021	120,065	Development service			
575	07.07.2021	20	Food, beverage, tabacco			
659	16.07.2021	234,954	Development service			

Curriculum Vitae

Since 12/20	CARIAD SE, a Volkswagen Group Company in Berlin, Germany Lead Purchasing Analytics and Steering
Since 10/18	University of Mannheim in Mannheim, Germany Doctor in Business Administration at the Business School (initially in the Data and Web Science Group)
09/22 - 12/22	Massachusetts Institute of Technology in Cambridge, MA (USA) Sloan Visiting Fellow Research Stay
06/16 - 11/20	Dr. Ing. h.c. F. Porsche AG in Stuttgart, Germany Partner Manager Smart Mobility
09/14 - 12/15	German Academic Exchange Service in Beijing, China Postgraduate Fellow Language and Professional Training in China
10/12 - 08/14	Karlsruhe Institute of Technology in Karlsruhe, Germany Master of Science in Production and Operations Management
10/12 - 08/14	International Business Machines in Mainz, Germany Project Buyer Smart Energy
09/11 - 08/12	Robert Bosch GmbH in Waiblingen, Germany Logistics Planer
09/09 - 05/11	Simpson College in Indianola, Iowa (USA) Bachelor of Arts in International Management