Journal Pre-proof

Artificial intelligence and machine learning in purchasing and supply management: A mixed-methods review of the state-of-the-art in literature and practice

Jan Martin Spreitzenbarth, Christoph Bode, Heiner Stuckenschmidt

Please cite this article as: Spreitzenbarth, J.M., Bode, C., Stuckenschmidt, H., Artificial intelligence and machine learning in purchasing and supply management: A mixed-methods review of the state-of-the-art in literature and practice, *Journal of Purchasing and Supply Management* (2024), doi: https://doi.org/10.1016/j.pursup.2024.100896.

Artificial intelligence and machine learning in purchasing and supply management: A review of the literature with expert interviews

Jan Martin Spreitzenbarth[12]

Tachenbergstr. 29C, 70499 Stuttgart, Germany

Jan.spreitzenbarth@uni-mannheim.de

Prof. Dr. Christoph Bode[1]

Bode@bwl.uni-mannheim.de

Prof. Dr. Heiner Stuckenschmidt[2]

Heiner@informatik.uni-mannheim.de

[1]University of Mannheim

Endowed Chair of Procurement, Business School

L5 5, 68161 Mannheim, Germany

[2]University of Mannheim

Data and Web Science Group, School of Business Informatics and Mathematics

B6 26, 68159 Mannheim, Germany

You may address all correspondence concerning this manuscript at: jan.spreitzenbarth@uni-mannheim.de.

**Artificial intelligence and machine learning in purchasing and supply management:
A mixed-methods review of the state-of-the-art in literature and practice**

ABSTRACT

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 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. This is the first systematic review in the area of operations and supply chain management utilizing the Computer Classification System as the de facto standard in computer science for clarity in the terminology of these emerging technologies. In matching the literature search with the interview results, a mismatch was found between the reviewed literature and the expert's assessments. For instance, the cluster cost analysis deserves higher research attention as well as supplier sustainability. Moreover, there seems to be a gap in the operational area, which many believe to be first considered due to data availability. The insights may guide researchers and executives to better understand the dynamic capabilities needed to successfully steer the organization in the transformation toward procurement 4.0.

Keywords: Artificial intelligence; machine learning; digital transformation; procurement; mixed-method research method; literature review

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; Flechsig et al., 2022). There is a need to evaluate, structure, and provide insights on the increasing research and practical activities of emerging artificial intelligence (AI) and machine learning (ML) 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. This is significant because only a few public and private purchasing organizations have successfully integrated these evolving technologies into their operations and across their supply chains.

Next to general studies of big data analytics in operations and supply chain management, there are distinct reviews of AI and ML in the neighboring domains of production, and logistics; however, for the field of purchasing and supply management (PSM), there is not yet an exhaustive and systematic review published in a peer-reviewed journal. The closest work Guida et al. (2023) has recently been published in the Journal of Purchasing and Supply Management, where the current offerings of information technology providers are mapped to an established purchasing process model and directions for future research set out. In addition, Meyer and Henke (2023) developed ten general design principles for the application of artificial intelligence and machine learning technologies in procurement.

While other related works are structured around various terms of applied algorithms and explore their applications as well as strengths and weaknesses, the main objective of this inductive review is to 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). Overall, practitioners and academics seek to understand which technologies perform what types of tasks and best address specific needs to increase procurement's value proposition (Seyedghorban et al., 2020) leading to the research question:

- **RQ: What is the state-of-the-art in literature and practice of artificial intelligence and machine learning in purchasing and supply management?**

Following the paradigm of pragmatic science as advocated for instance by Tranfield et al. (2003), this work seeks to combine the rigor of a systematic review of the literature with relevant practical insights through twenty expert interviews from in total of seventeen different organizations in order to triangular the results. This work thereby offers an overview of the state-of-the-art literature and practice, whereby 46 works published in 30 different mediums meeting the inclusion criteria from 1989 to 2020 were classified into 11 procurement use case clusters. In seeking an answer to the research question, the engagement of different perspectives is necessary. Academic and practitioner data is thereby combined synergically to study the emergent, problematic phenomenon of the adoption of AI and ML in PSM because it appeals simultaneously to different communities of practice, each with its own institutional practices, wordings, definitions, routines, and publication outlets. As argued for instance by Simsek et al. (2018), the two knowledge systems can become complementary, if methodological rigor is meticulously applied.

The main contributions of this research are threefold: Firstly, this is the first known review at the cross-section of operations and supply chain management with computer science to apply the ontology of the Computing Classification System (CCS) of the Association for Computing Machinery (ACM) as the de facto standard to strengthen the comprehension for the coding, what types of technologies have been applied. Secondly, in matching the literature search with the interview results, a mismatch was found between the reviewed literature and the expert's assessments. For example, the cluster cost analysis requires more research attention. Moreover, there seems to be a gap in the operational area, which many believe to be first considered due to data availability. Thirdly, the works meeting the inclusion criteria were mainly published in technical publications. Thus, this work intends to encourage scholars to publish their works in PSM-focused outlets to disseminate knowledge in this field and thereby create a stronger basis of common terminology.

The remainder of this article is organized as follows: The next section describes the theoretical background of the paper. Afterwards, the methodological approach is outlined. This is followed by content analysis from the material collection, descriptive analysis, to category selection with boundary conditions and common themes as well as the cluster evaluation through expert interviews. Then, the material evaluation is conducted along the strategic, tactical, and operational levels for both direct and indirect procurement. Finally, the results are discussed, and the conclusions are summarized with contributions to theory and practice as well as limitations and opportunities for future research.

2. Theoretical background

The digital transformation is not an end but must provide value to the organization to justify the investment. Dynamic capabilities theory is often applied to better understand digital technological adoption (Spina et al., 2016; 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). Purchasing is an essential operations and supply chain management process with a significant impact on the overall success of the organization across different sectors of the economy, as suppliers typically account for more than fifty percent of the generated value (Schuh et al., 2023).

The adoption of digital technologies in purchasing impacts its organization, processes, and capabilities. As the PSM function evolves from a former reactive and supportive stance into a more strategically embedded role with the organization actively managing the supply base, professional buyers need to embrace technological advancements (Bals et al., 2019; Flechsig et al., 2022). Yet, organizations face challenges in acquiring skilled personnel, addressing employee concerns, and cultivating a receptive culture (Meyer and Henke, 2023). 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).

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 (Bienhaus and Haddud, 2018). Following van Weele (2018), 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. As pointed out for instance by Guida et al. (2023), recent advances in AI and ML technologies may not only automate and augment essential procurement processes, but also could have severe implications for how procurement organizations are structured and governed, buyers are hired, trained, and interact with external suppliers and internal stakeholders. This pertains to the "*redefinition of the purchasing function, of the purchaser's role, of supplier relationship management policy, and of interdepartmental collaboration*" (Allal-Chérif et al., 2018, p. 69).

Most researchers agree that humans and computers possess complementary abilities that can enhance each other. If implemented well, leveraging the potential of artificial intelligence and machine learning technologies could become a major power factor in the future, especially in the interaction with external partners and thus buyer-supplier relationships (Nitsche et al., 2021a; Spreitzenbarth et al., 2022). For instance, one common design approach is to automatically learn by observing human behavior. The social network Facebook has used this approach to train autonomous negotiating agents with the unintended consequence that they learned to lie (Gratch, 2021). In addition, the models started to negotiate in their own language which has been compared to the way humans create abbreviations. 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 scientific and popular interest but also continued criticism of inherent biases.

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 and is understood as typically understood as the study of computer algorithms that improve through experience using data (Russell and Norvig, 2020).

3

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. In addition, this work utilizes the CCS visualized in Fig. 5 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), where about sixty percent of the articles meeting the inclusion criteria of this review can be attributed to machine learning. To enrich the review with relevant practical insights from the interviews, power quotes are inserted throughout the study as below where some have been slightly adjusted for better readability.

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."*

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 enterprise resource planning system to a disjoint contract management system (Schulze-Horn et al., 2020). For instance, Flechsig et al. (2022) studied their potential as well as hurdles and success factors for implementation in terms of technological, organizational, and environmental readiness in procurement organizations. 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 to achieve better performance (Gunasekaran et al., 2017). Most scholars agree that AI and ML in PSM are still in an early maturity stage (Bienhaus and Haddud, 2018; Schulze-Horn et al, 2020; Allal-Chérif et al., 2021; Nitsche et al., 2021a; Bodendorf et al., 2022; Cui et al., 2022a; Burger et al., 2023; Guida et al., 2023; Meyer and Henke, 2023) requiring further research and practical applications to make their potential accessible for procurement organizations.

3. Material and methods

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 of Mayring (2014) 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. Simsek et al. (2018) stressed that academics and practitioners see in diverse ways. In addition, Thomé et al. (2016) emphasized the significance of broadening the scope of research beyond keywords to ensure inclusivity, advocating to seek expert opinions and conduct both backward and forward snowball searches to enhance comprehensiveness in the search process. Hence, interviews with experts of different organizations have been conducted to evaluate the deducted use case clusters from the literature as well as enrich the review with practical insights in order to triangular the results as "*it is a specific strength of content analysis that this method can combine qualitative approaches retaining rich meaning with powerful quantitative analyses*" (Seuring and Gold, 2012, p. 546). Overall, this led to a mixed-methods research approach combining quantitative and qualitative aspects of both the systematic literature review and the expert interviews to find an answer to the research question.

The state-of-the-art artificial intelligence and machine learning in purchasing and supply management is arguably in a nascent phase, for this phase inductive theory building is proposed

as appropriate by 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. 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 AI and ML in PSM. 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 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 (Durach et al., 2017).

3.1 PRISMA statement

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 (PRISMA), as utilized for instance by Bäckstrand et al. (2019), whereby the numbers of publications are shown in brackets.
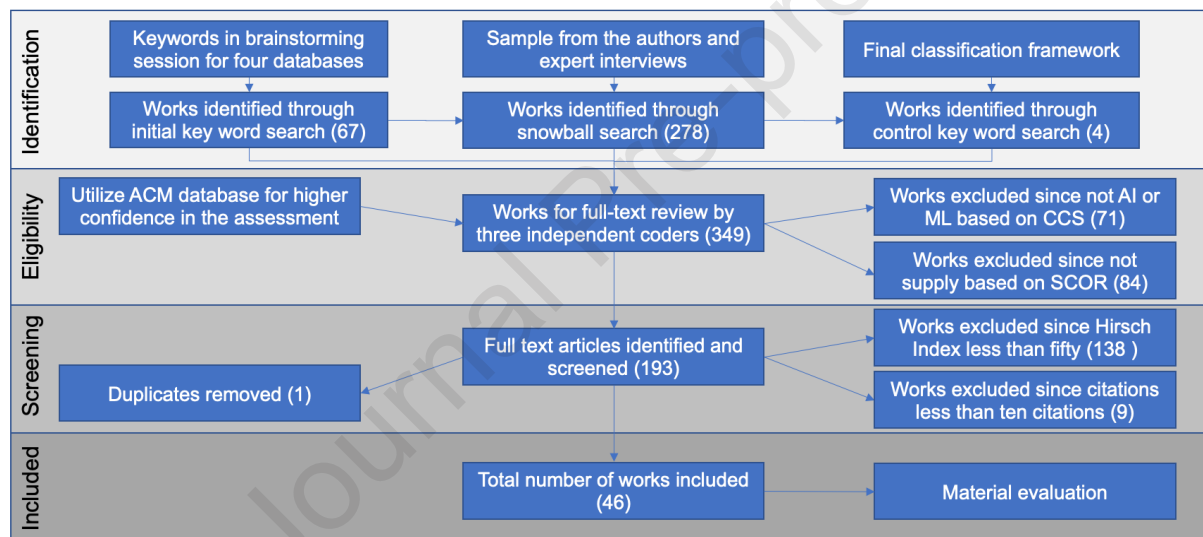

Fig. 1. Overview of the review process (own illustration based on Page et al., 2021).

The work was carried out 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, which is illustrated in Fig. 4 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).

Furthermore, inclusion criteria were iteratively devised as the literature was more fully understood. An established framework from the field of computer science was utilized as a clearly defined ontology with precise terminologies. Similarly, the Supply Chain Operations Reference (SCOR) model of the professional society Association for Supply Chain Management (ASCM) has been employed. Three independent coders classified the literature according to the CCS and the SCOR frameworks 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 (van Weele, 2018; Vollmer et al., 2018) with an open investigation in search of main themes.

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 in version 7, 84 were excluded since they did not explicitly address supply issues according to the SCOR model in version 13, 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 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. 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 from 1989 to 2020 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 over for instance Scopus despite its shortcomings in terms of adjusting the results based on previous searches. After examining other literature reviews in the field and carrying out a sensitivity analysis like with the publication outlet's scientific impact criteria, the citation bar was set comparatively low since much research has been 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 referred to such as 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 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).

3.2 Material collection

The keyword set was set up by examining other reviews in the extant literature on big data analytics in operations and supply chain management 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 as summarized in the PRISMA statement. Using more than one database to identify relevant literature contributes to preventing any research from

being missed and reducing any possible publication biases (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 based on the standard search engine settings, which typically contains metadata including title, abstract, and keywords.

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 query keywords were first varied in different ways and several search databases were tried. In addition, 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 broad technology-focused journals than in supply-focused journals.

In total, 71 articles were identified that served as the basis for forward and back searches to ensure an exhaustive review (Thomé et al., 2016; Durach et al., 2021) in addition to the sample of the authors and the interviewed experts leading to 349 articles. This led to a major finding of this review that there is still a lack of common definitions for the application of AI and ML in PSM. Finally, 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 and that also marks the cutoff date of the search. Although literature reviews are likely never complete, this provides some evidence that it has reached a certain degree of comprehensiveness.

3.3 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 the final 46 works based on the inclusion criteria described in the PRISMA statement and of all 349 identified works along with the free-text categories listed at the bottom of the table.

Table 1
Overview coding scheme for the review of the literature.

Category (if applicable following)	Type with publication count in declining order (meeting inclusion criteria/ all identified works)
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, 2020)	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 (46/46)
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 preceding table, most works meeting the inclusion criteria do not explicitly mention applied theories, but several works are theoretically based on fuzzy logic, transaction cost economics, and game theory. In addition, a number of works distinctly focus on concrete applications in particular of manufacturing, transportation, and construction but

8

most works are rather abstract and not directed toward the particulars of specific use cases or industries. The organizational setting for most of the research is on larger organizations in general, while some focus specifically on public procurement. Yet, no work meeting the inclusion criteria 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) combines sustainability and supplier selection based on a machine learning technique. Thereof, only six works have a female lead author. 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. Furthermore, 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 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 research methods in the figure below. Overall, there is a wide spread of 30 different mediums mostly from technical-oriented journals and the wider operations and supply chain management 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 search was conducted in the Journal of Purchasing and Supply Management or Supply Chain Management: An International Journal.
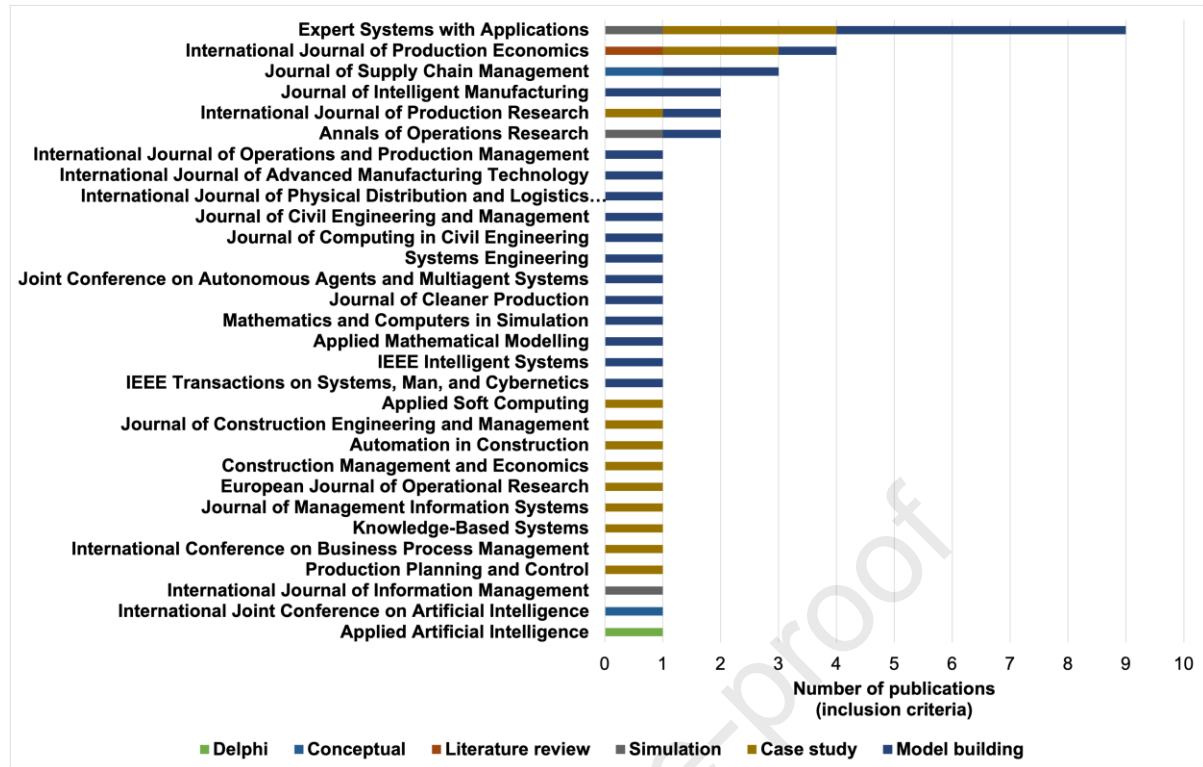
Fig. 2. Overview of publication mediums of the works meeting the inclusion criteria.

Time analysis has been performed on the 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) or Suurmond et al. (2023) illustrated in the figure below. The bars represent the publication number of the strategic, tactical, and operational levels of procurement, whereby the grey line symbolizes AI and the yellow line ML technologies. As of submitting this work, the last lustrum is likely to continue the constantly rising trend of the increasing number of publications of the last years.
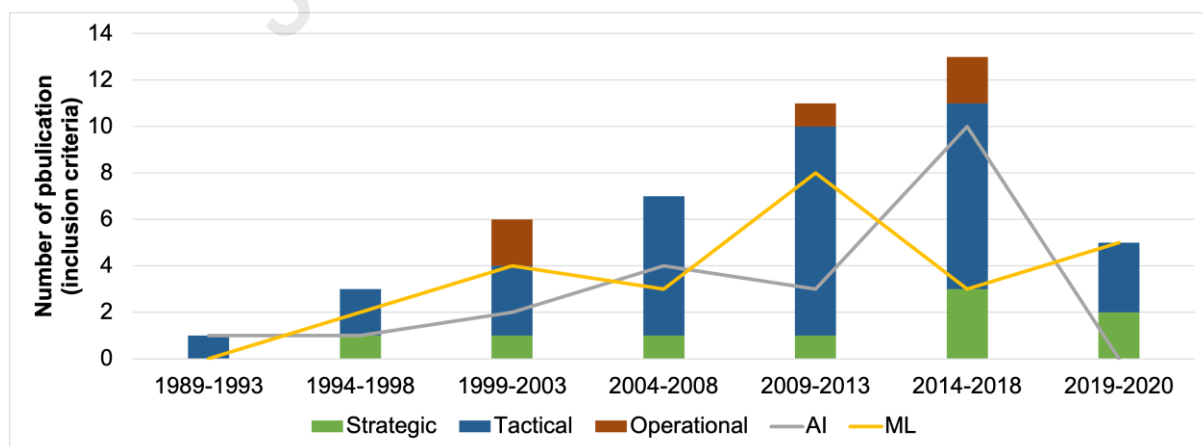
Fig. 3. Number of publications of AI and ML in PSM in temporal buckets.

The works meeting the inclusion criteria are spanning 32 years from 1989 until 2020. 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 to AI and ML in PSM could be identified during the systematic search.

10

Some may argue that an over thirty-year-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. In addition, as described in the theoretical background, the recent technological advancement of AI and ML is not a new phenomenon but rather a reemergence of a prominent set of technologies connected with high hopes but also deeply ingrained fears.

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). 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. Moreover, as summarized in Table 1 above, several CCS classes have seldom been applied so far in purchasing and supply management such as cross-validation, computer vision, or planning and scheduling.

3.4 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, the Supply Chain Operations Reference model has been utilized as a process-oriented framework for academic analysis for instance in Brinch (2018) and Chehbi-Gamoura et al. (2019). It describes six primary operations and supply chain management activities, whereby the supply function is understood as processes that procure goods and services to meet demand (ASCM, 2020). This general understanding is detailed using the strategic, tactical, and operational levels of procurement as the starting point for the search for common themes as described in the methodological section. Thereby, 11 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

One model that is commonly utilized to depict major procurement processes is the Extended Purchasing Process as a wheel of iterative processes with supplier relationship and performance management in its midst (van Weele, 2018). 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. In the figure below, the identified use case clusters are mapped to the Extended Purchasing Process model with the strategic level in light grey coloring, the tactical level in orange coloring, and the operational level in light yellow coloring.
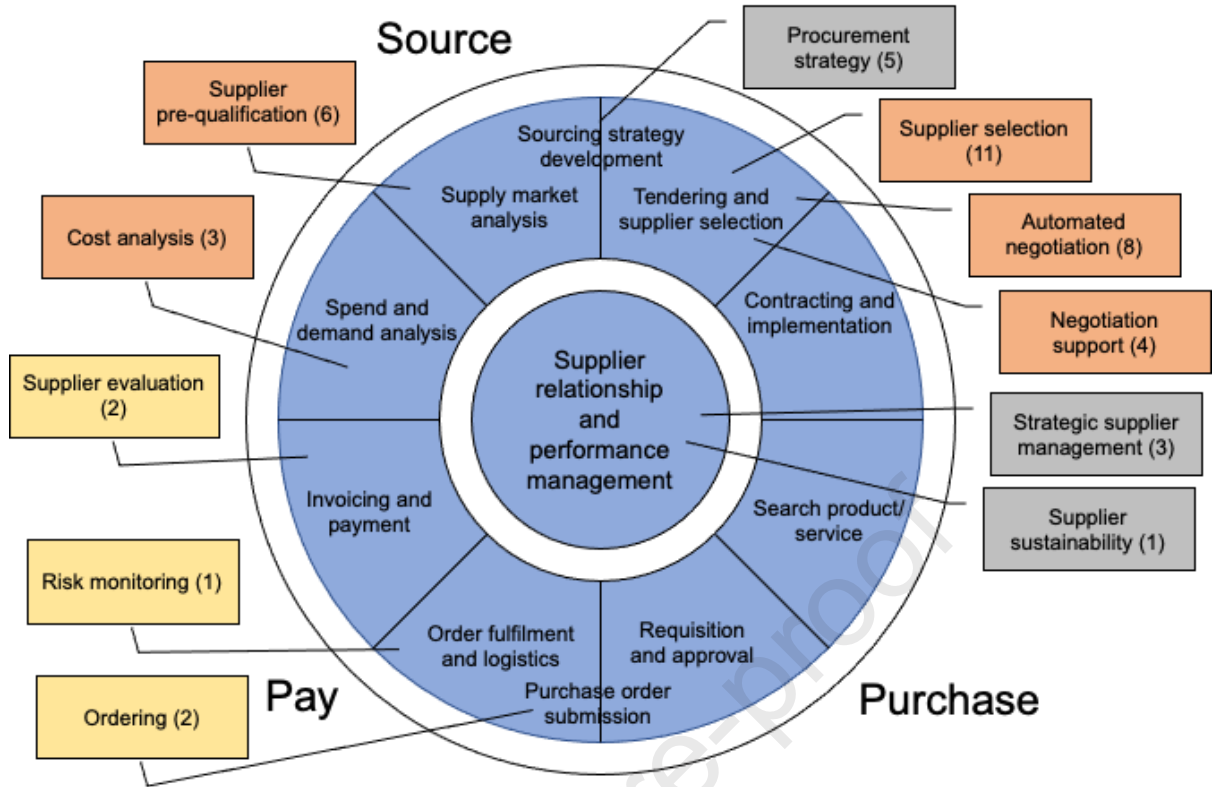
Fig. 4. Use case cluster mapping (own illustration based on van Weele, 2018).

Secondly, according to the Computing Classification System as an up to six-tiered hierarchical ontology, AI and ML are sub-categories of computing methodologies as computer-assisted analysis and processing of problems in a particular area. Ontologies are modular representations of knowledge and are well-established in computer science. The CCS has been applied as a classifier for digital libraries such as by ACM or CiteSeerX and in some technical literature reviews like Frolov et al. (2020).

The tiered structure of the ontology is visualized below, which highlights the level 3 classes of artificial intelligence and machine learning.
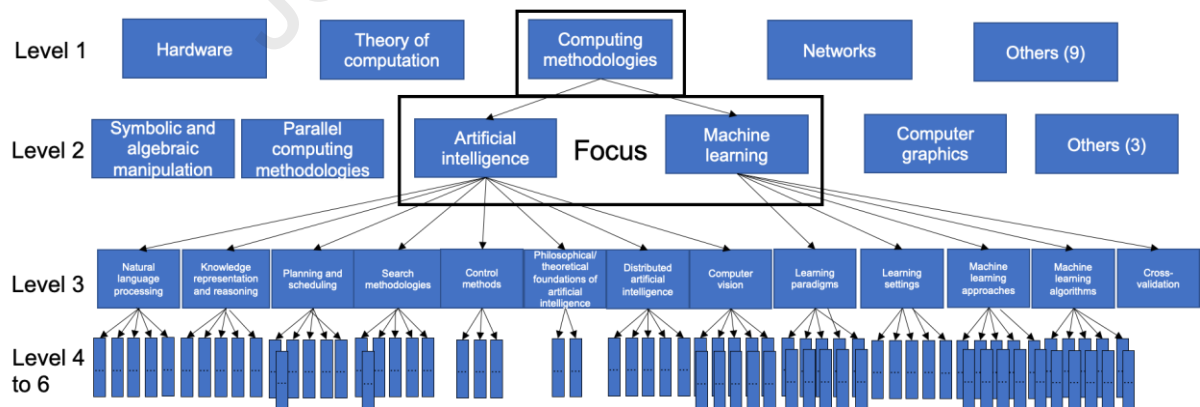

Fig. 5. Computing Classification System (own illustration based on ACM, 2012).

There are thirteen level 1 and eight level 2 classes for computing methodologies. 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

12

- 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

Machine learning includes these 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, eight were directly classified with pronounced confidence based upon the "ACM Guide to Computing Literature" with over three million mainly technical entries, whereby most 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 Fig. 1. In five instances, the classification of the work in the ACM database was not followed after intensive discussions between the coders. Finally, 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 computing science is becoming ubiquitous.

3.5 Triangulate results

Based upon the research question 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-ended questions (McCracken, 1988; Mayring, 2014). In total, twenty-nine persons were invited, whereof twenty interviews were conducted from in total seventeen different organizations between October 19th, 2020 and March 24th, 2021 to enrich, compare, and contrast the findings from the analysis of the literature.

The interviewees 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, whereby one interview was conducted per case online taking between 45 and 60 minutes by at least two researchers. The interviews took place amid the coronavirus pandemic disrupting supply chains worldwide but also fostering digitalization initiatives, which may have skewed the assessment more toward supply chain resilience and transparency factors. The sample includes a variety of different professional backgrounds in terms of organizational type,

country headquarters, and number of employees as well as level of hierarchy as summarized in Table B.1. In addition, further factors were taken into consideration such as age and gender to capture a holistic picture of diverse points of view. Moreover, sampling bias and selection bias were remedied by involving multiple researchers (Seuring and Gold, 2012). Also, non-responsive bias was addressed by follow-ups and iteratively, purposefully selecting further experts until saturation in the interview assessment was reached.

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. 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). As part of the expert interviews, a quantitative assessment of the derived use case clusters from the literature has been conducted in order to triangulate the results. The summary statistics are shown in the table below along with their standard deviations σ and average values μ. A definition of each of the clusters was provided in the interview guideline with the expert interview invitation along with the sub-dimensions of 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 adapting an approach of a consultancy report on the topic by Ziegler et al. (2019).

Table 2
Summary statistics of the use case cluster assessments 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**

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). 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

14

practical applications that arose during the interview session. The guideline and anonymized interviewee list in chronological order are provided in the Appendices.

Thomé et al. (2016) highlight that research outcomes can be standardized using statistical methods, allowing for their transformation into a unified metric. To match the research activity with the results of use case assessments in the expert interviews, the following equations were used to create Fig. 6 in the discussion section. Firstly, the research activity has been calculated by multiplying the number of publications of the use case cluster by the number of citations.

Equation 1
Research activity of the use case clusters.

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

Secondly, the aggregated expert assessment of each use case cluster can be calculated by the three sub-dimensions of the business value and ease of implementation. In total six assessed aspects were given equal weights in the formula below as the evaluation of different use cases can be approached by considering their potential business value as well as their implementation, maintenance effort, and data availability. In addition, it was apparent in the expert interviews that the sub-dimensions are fairly balanced, and not one factor is decisive over the others as summarized in Table 2 above.

Equation 2
Attractiveness of the use case clusters.

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

Thirdly. 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.

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

Lastly, the mixed-method review started with the data search, whereby the coding scheme and the interview guideline were developed and continuously improved when the first data exploration and the interviews took place simultaneously in an iterative process. The research thereby started with a broad term of artificial intelligence, which is still apparent in the semi-structured interview protocol. Following open science principles, the data from the analysis of the literature and the interviews can be found under a Creative Commons license as data references for future research with publication. Thereby, no specialist software was used other than Microsoft Office tools and in-depth discussions among the coders. In addition, natural language processing technologies have only been used to improve the writing for better readability, such as checking grammar and spelling.

4. Material evaluation

The material is described along the strategic, tactical, and operational dimensions as outlined in the methodology with empirical insights from the conducted expert interviews and relevant popular studies. The procurement use case cluster and Computing Classification System class of the 46 works meeting the inclusion criteria are marked with bold script in this section.

4.1 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. Artificial intelligence and machine learning "*applications can help PSM to realize its role as a value driver in the company, as operational processes can be automated and strategic processes can be supported*" (Meyer and Henke, 2023, p. 2). The strategic works meeting the inclusion criteria are enlisted in alphabetical order by cluster, the applied research method, and the Computer Classification System level 3 categorization in the table beneath.

Table 3
Overview of the strategical works meeting the inclusion criteria.

Cluster	Publication	Research method (adapted from Spina et al., 2016)	CCS class (ACM, 2012)
Procurement strategy	Abolbashari et al. (2018)	Case study	Knowledge representation and reasoning
	Cheung et al. (2004)	Model building	Distributed artificial intelligence
	Choi et al. (2018)	Simulation	Knowledge representation and reasoning
	Lorin (1997)	Conceptual	Machine learning approaches
	Veit et al. (2017)	Case study	Learning settings
Strategic supplier management	Cavalcante et al. (2019)	Simulation	Learning paradigms
	Choy et al. (2002)	Case study	Machine learning approaches
	Pournader et al. (2019)	Case study	Machine learning approaches
Supplier sustainability	Kuo et al. (2010)	Model building	Machine learning approaches

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). 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). Furthermore, 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). In general, an intelligent procurement assistant like an enterprise version of ChatGPT could provide a relevant 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. 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.

16

When asked about data, expert IX stated: *"We often work with qualitatively bad data and not much data at all. Digitalization must be seen 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). In addition, 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, i.e., through partnerships with key suppliers (Nitsche et al., 2021b), i.e., an algorithm anonymously collects data to train a common predictive model for better inventory management. 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.

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, Prewave a start-up from Austria 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). 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). Overall, sustainability was one of the use cases with a stark difference in opinion in the interviews. While see its business value mainly in marketing purposes, other experts 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. This aligns well with the recent call for papers by the Journal of Purchasing and Supply Management "Digitalization for Sustainable Purchasing and Supply Chain Management".

4.2 Tactical level

Comparatively many publications can be attributed to supplier pre-qualification, cost analysis, negotiation support, automated negotiation, and supplier selection. Earlier surveys such as Tata Consultancy Services (2016) show that these emerging technologies have already been adopted to automate sourcing processes, for example by recommending new potential suppliers in public and private organizations worldwide.

Table 4
Overview of the tactical works meeting the inclusion criteria.

Cluster	Publication	Research method (adapted from Spina et al., 2016)	CCS class (ACM, 2012)
Supplier pre-qualification	Choy et al. (2003)	Case study	Machine learning approaches
	Lam et al. (2011)	Case study	Machine learning approaches
	Jain et al. (2014)	Model building	Learning paradigms
	Khoo et al. (1998)	Model building	Knowledge representation and reasoning
	Plebankiewicz (2009)	Model building	Knowledge representation and reasoning
	Wu and Barnes (2012)	Model building	Machine learning approaches
Cost analysis	Caputo and Pelagagge (2008)	Model building	Machine learning approaches
	Chou et al. (2015)	Case study	Machine learning approaches
	Degraeve et al. (2004)	Case study	Knowledge representation and reasoning
Negotiation support	Carbonneau et al. (2008)	Model building	Machine learning approaches
	Matwin (1989)	Model building	Knowledge representation and reasoning
	Schulze-Horn et al. (2020)	Delphi	Machine learning algorithms
	Sim et al. (2009)	Model building	Distributed artificial intelligence
Automated negotiation	Baarslag et al. (2017)	Conceptual	Distributed artificial intelligence
	Guo et al. (2009)	Model building	Machine learning approaches
	Guosheng and Guohong (2008)	Model building	Machine learning approaches
	Hindriks and Tykhonov (2008)	Model building	Distributed artificial intelligence
	Lin et al. (2011)	Model building	Knowledge representation and reasoning
	Moosmayer et al. (2013)	Case study	Machine learning approaches
	Oliver (1996)	Case study	Machine learning approaches
	Son et al. (2014)	Model building	Knowledge representation and reasoning
Supplier selection	Ferreira and Borenstein (2012)	Simulation	Knowledge representation and reasoning
	Hosseini and Barker	Case study	Knowledge representation and

18

	(2016)		reasoning
	Luan et al. (2019)	Model building	Machine learning approaches
	Lee and Ou-Yang (2009)	Model building	Machine learning approaches
	Kang et al. (2012)	Model building	Learning paradigms
	Kashiwagi and Byfield (2002)	Case study	Distributed artificial intelligence
	Moghadam et al. (2008)	Case study	Control methods
	Wu and Barnes (2016)	Case study	Knowledge representation and reasoning
	Vahdani et al. (2012)	Model building	Machine learning approaches
	Venkatesh et al. (2019)	Model building	Machine learning algorithms
	Yücenur et al. (2011)	Model building	Knowledge representation and reasoning

Learning paradigms generally 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). 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 approaches 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., 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, a case study of the bundling problem has been conducted with an automotive software organization utilizing forward-looking procurement planning data of requisitions to recommend to the buyers potential saving opportunities (Spreitzenbarth et al., 2024). 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). 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 utilize collaborative filtering and content-based filtering techniques to assist industrial buyers in discovering relevant information (Park et al., 2011). In addition, natural language processing can aid in master data management such as eliminating duplicate supplier entries, rectifying misspellings, classifying requisitions and invoices, and aggregating spending data from individual group companies into the holding structure (Sammalkorpi and Teppala, 2022). Moreover, 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 development stages, engineers can substantially reduce the total cost by querying the model with updated high-level product attribute data to guide them through the conceptual design at target cost.

When asked about other relevant applications, 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 intense 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, Bayesian learning and genetic algorithms as **distributed artificial intelligence** can support negotiations with incomplete information (Sim et al., 2009) and expert systems may be able to adequately address complex negotiation 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 example 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 (Schuh et al., 2022).

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

20

America (Kahn, 2021). 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) such as 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 example in the automotive supply chain (Automated Negotiation SCM Consortium, 2023). Yet, 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 several principal organizations prefer that their negotiation agents employ ethically questionable tactics such as withholding information and emotional manipulation. Overall, the expert assessment of this use case cluster 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. Machine 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. To sum up, human-machine results are promising (Cui et al., 2022a; Saenz et al., 2022) with a myriad of questions for future research.

Expert XX questioned, *"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 be accurate for a number of instances, it does not necessarily apply for all types of requisitions: *"An interesting use case is automated negotiation especially of smaller requisitions as the long tale of spend 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. 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 function 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 on other use cases, particularly in the operative area.

4.3 Operational level

Many expect AI and ML to be implemented in operative areas first, however, there are few works on operational use cases as illustrated in Fig. 3. The identified operational publications mainly cluster around risk monitoring, ordering, and supplier evaluation.

Table 5
Overview of the operational works meeting the inclusion criteria.

Cluster	Publication	Research method (adapted from Spina et al., 2016)	CCS class (ACM, 2012)
Risk monitoring	Nepal and Yadev (2015)	Case study	Knowledge representation and reasoning
Ordering	Bodaghi et al. (2018)	Model building	Knowledge representation and reasoning
	Faez et al. (2009)	Literature review	Machine learning approaches
Supplier evaluation	Narasimhan et al. (2001)	Model building	Machine learning approaches
	Shore and Venkatachalam (2003)	Model building	Knowledge representation and reasoning

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 networks as **knowledge representation and reasoning** have 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). Finally, 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 the 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 navigate through the **ordering** process as part of a guided buying information technology system but also answer standard questions from the supply base (Botfriends, 2023). 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, capacity and contract data can be matched with orders 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 of engineering, sustainability, 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). Lastly, supplier quality management could benefit from analyzing defects in the inbound quality control to deduct process and product improvements while reducing quality costs.

5. Discussion

As outlined in the introduction, the engagement of different perspectives is essential in order to find a holistic answer to the research question. 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 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 to facilitate current and further use cases (Herold et al., 2022). Particularly experts from large 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. No sector-specific bias was apparent, however, principally, the pain points and technological solutions of large organizations public or private alike were quite different than those of comparatively smaller organizations. Moreover, it was evident during the literature search that there are relevant applications in public organizations that may be applicable to private organizations and vice-versa without a strong indicator that one is further ahead of the other. Similarly, many of the identified use cases are relevant for direct and indirect procurement.

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."* 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, but particularly for new challenges such as sustainability that are prone to data-driven decision-making, such as risk management and negotiation. For instance, data on sustainability such as by EcoVadis that can be utilized by analytical models is becoming more readily available in addition to software-on-demand solution providers like Prewave. As Markus Wagner, Head of Procurement Strategy and Sustainability at Porsche pointed out "*for us, this is about transparency. Artificial intelligence simplifies the complex analysis of data, allowing us to address partners directly and request improvements in sustainability*". 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, several 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. (2022), and Burger et al. (2023).

Overall, the experts showed a preference for approaching the application of AI and ML in PSM from the business value while considering the organizational strategy, current information systems landscape, data quality, and available talent. While some experts highlighted that AI and ML support human decision-making for instance through recommendation systems augmenting the skills of buyers, others are open for example to autonomous negotiation agents that can make their own decisions whereby humans focus on parameter tuning and oversight (Moosmayer et al., 2013). 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*

24

people cannot think in a multidimensional space but machines are made for that" (Murray, 2022). In addition, autonomous agents may be unbiased and could potentially be free of unethical behavior. For instance, a negotiation bot for a public or private organization does not receive gifts or free entertainment that could influence a supplier selection decision. Generally, machine learning approaches such as neural networks are widely researched especially for automated negotiation. Knowledge representation and reasoning is extensively utilized especially for dealing with uncertainty in supplier selection, and distributed artificial intelligence is often applied for examining the actions of multiple agents.

However, overall, there is comparatively more research activity for the clusters automated negotiation and supplier selection than how the business value and the ease of implementation have been assessed in the expert interviews. Measuring the research activity following Equation 1 in the methodological section by multiplying the number of publications of the cluster with the number of citations, the largest cluster is on supplier selection, where many different frameworks have been proposed by literature to select the right suppliers based on data-driven algorithms. Measuring the use case cluster attractiveness following Equation 2, by aggregating the respectively three sub-dimensions of the business value and ease of implementation through the expert interviews, among the most attractive clusters are cost analysis and operational use cases grouped in risk monitoring, ordering, and supplier evaluation. The research activities from the material evaluation are matched with the results of the interviews following Equation 3. 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 beneath.
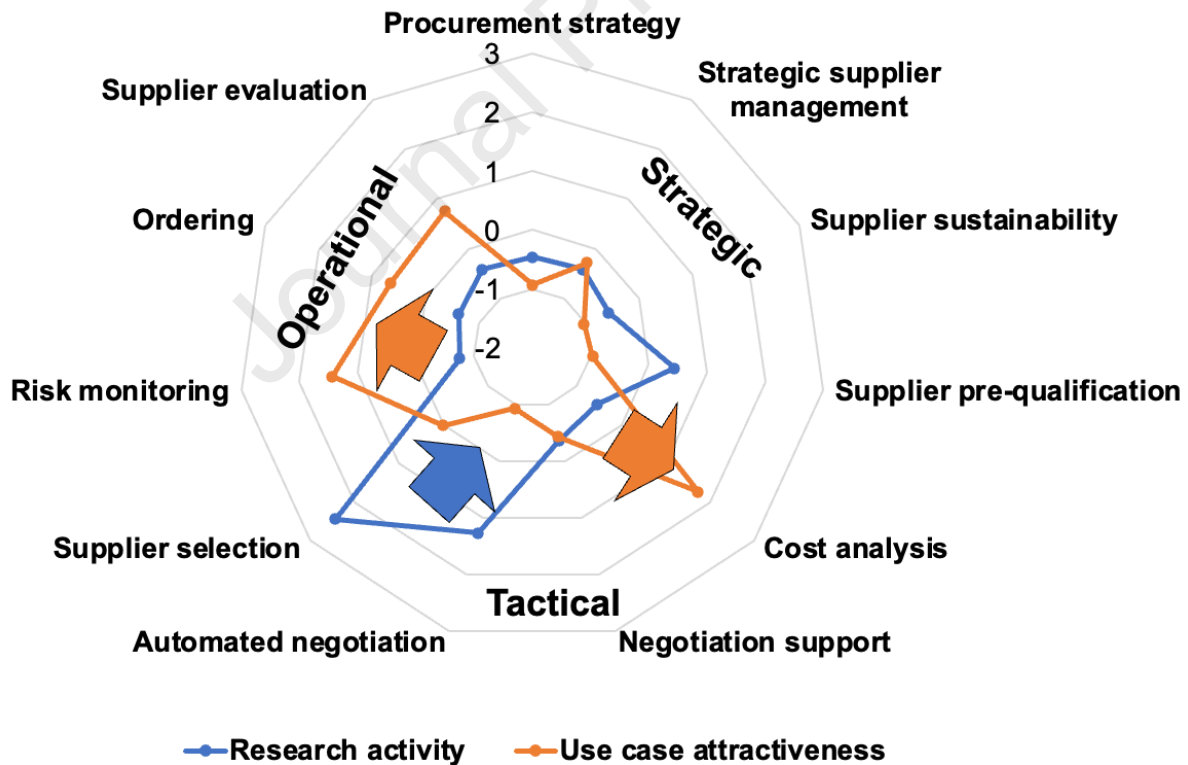

Fig. 6. Comparing research activity and cluster attractiveness of the identified clusters.

As visualized above, the application of artificial intelligence and machine learning technologies in the operative area of procurement necessitates more research attention. In addition, it is compelling that some clusters are not yet well researched if at all described by popular publications. This restricts the extent of a systematic literature review; however, this limitation is likely to be overcome with more research and implementation. For instance,

25

similarity analysis of parts based on specifications and technical drawings could yield substantial savings due to the reduction of variations and complexity. In addition, 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). For example, 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 may 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 end-to-end 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 a crucial 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, by which the costs for training and model maintenance must be taken into consideration. This is consistent with the aforementioned Deloitte survey, whereby most organizations acquire solutions rather than building them in-house (Mittal et al., 2022) for example 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 enterprise resource planning 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 particular, 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).

Furthermore, the former leader of the AI and ML research groups at the search engine providers Google and Chinese 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 with their internal and external stakeholders to use the technology, most experts agreed that new talent must be hired in order to effectively introduce and manage the emerging

26

technologies. This fits with the findings of Bals et al. (2019) that identified competencies related to sustainability and digitization are becoming increasingly essential for future PSM professionals. Another 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.

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 business-to-business not enough data, business-to-consumer 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 technological 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 (Vollmer et al., 2018; Ziegler et al., 2019). 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. Finally, should academia start to support managerial AI or ML pursuits - or procurement managers start to use the potentials identified in the research? While this mixed-method review has shown that research still trails practice concurring with Allal-Chérif et al. (2021) and Guida et al. (2023) among others, this work intends to encourage pragmatic research following Tranfield et al. (2003) to foster an evidence-informed digital transformation of public and private procurement organizations worldwide.

6. Conclusion

This inductive mixed-method review offers an overview of artificial intelligence and machine learning in procurement with 46 works from 1989 to 2020 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 the results of the systematic literature search with the expert assessment, alignment but also mismatch were apparent as visualized in Fig. 6. The cluster cost analysis requires 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 the usage of negotiation bots. Moreover, 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. If the technology is to fulfill the promise of not just effectively complementing the skills of buyers but also freeing them of repetitive, mundane tasks, more research and practical applications are necessitated for operational purchasing activities.

6.1 Theoretical contributions

The developed classification framework combines commonly accepted models from operations and supply chain management and computer science 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 practitioners' points of view in the analysis of the literature. In addition, this is the

27

first known review to apply the Computer Classification System that is visualized in Fig. 5 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 thereby started with the umbrella term "AI" in mind, but for clarity in the discussion e.g., if an algorithm is considered as artificial intelligence, machine learning, or another kind of computational method, it was decided to choose this de facto standard from computer science as the researchers deemed the various understandings confusing and not useful to conduct a structured literature review.

Most works meeting the inclusion criteria can be attributed to machine learning with about sixty percent of publications and citations while a few classes of artificial intelligence have been seldom applied so far such as search methodologies and computer vision. As described in Table 1, most works in the current nascent state of research do not explicitly mention theories, yet several 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 can be characterized as rather general and not directed toward the particulars of specific use cases or industries.

The publications meeting the inclusion criteria 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 Fig. 2 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 about one hundred and sixty articles in over eight publication outlets. Similarly, Nguyen et al. (2018) identified close to one hundred papers on the encompassing theme of big data analytics in operations and supply chain management in almost fifty 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. Therefore, this work 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 definitions.

6.2 Practical implications

The state-of-the-art in artificial intelligence and machine learning is described with a myriad of potential applications along the strategic, tactical, and operational levels for both direct and indirect procurement, which are summarized in Tables 3, 4, and 5. 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 through investing in people, data, and technology. Moreover, having both the domain knowledge and the technology toolbox will be an important skill set for future buyers.

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 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.

6.3 Limitations and future research

Finally, as the keyword search did not lead to sufficient results, an extensive snowballing search had to be conducted in this early maturity stage of AI and ML in PSM. Four commonly used databases were explored to reduce possible biases; yet, for instance, Web of Science, Scopus, CiteSeerX, and the ACM Digital Library itself might have added more to the search. Thus, an extensive snowballing search needed to be conducted through forward and back searches of the initially identified works as described in the PRISMA statement in Fig. 1. The apparent lack of common terminologies could be improved by firstly utilizing established frameworks such as the Extended Purchasing Process or the Computing Classification System, i.e., for indexed keywords, and secondly by encouraging scholars to publish their works in PSM-focused publication mediums to form such common wording basis for these emerging technologies such as Guida et al. (2023) or Meyer and Henke (2023). As an example, Burger et al. (2023) described four case studies that may be assigned to the clusters ordering, supplier pre-qualification, risk monitoring, and cost analysis.

While the review of the literature has led to a generally positive outlook on the technology, hurdles for their successful implementation have been identified echoing the findings of related research. Key issues are discussed such as algorithm aversion, ethical considerations, data quality, model maintenance, integrity complexity, or finding the right talent, however, many challenges are not only unspecific to procurement and can be found in more general reviews such as in Wamba et al. (2021), but also typically pertain to the digital transformation in general. Furthermore, the Supply Chain Operations Reference model was primarily utilized as a demarcation line to other operations and supply chain management processes such as production or logistics in order to strengthen the accountability of the coding instead of just declaring that this paper is predominately focused on procurement topics instead of related make or deliver and return processes as sometimes the line can be blurry. For example, the article by Shore and Venkatachalam (2003) was on the edge between supply and enable processes. After discussions among the coders, the categorization was tilted toward supply since the paper primarily examines supplier evaluation within the supply chain network. Moreover, the framework offers a systematic account of purchasing and supply management activities and could be used for clarity in wording for use cases similar to the Computing Classification System of the Association for Computing Machinery. 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.

Moreover, although sampling bias and selection bias were remedied by involving multiple researchers and considering diverse perspectives in the expert interviews, there is still a certain degree of embeddedness in the researchers' network. Also, based on the focus of the research objective, the interviews enriched the systematic search of the literature with empirical insights, however, for instance, separately conducted cross-case analysis, world cafés, focus groups, multiple case studies, or surveys could yield further results. Additionally, while the Computing Classification System has proved useful for the purposes of this review, detailed definitions for each level 1 to 6 classification would strengthen its explanatory power, especially for scholars outside of the domain of computing science. Considering the current dynamics in the field, systematic reviews should be conducted regularly, for example, a review based on a natural language processing methodology could yield interesting insights especially when a higher level of maturity has been reached. Such literature analysis may build upon Suurmond et al. (2023) recently published in the Journal of Purchasing and Supply Management, where research clusters with their interlinkages were data-drivingly identified, and discussed how textual similarity and network analysis methods may be used in the research area.

Matching the literature and the empirical assessment of the expert interviews based on the quantitative measure following Equation 3, the cluster cost analysis deserves more research attention. Also, the results of the comparative analysis suggest deemphasizing AI and ML research on supplier selection, which is currently the most pronounced 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 essential negotiations are not likely to be fully automated soon.

Declaration of competing interest

The authors declare no conflict of interest, financial or otherwise.

References

Mendeley data reference of the analysis of the literature and the interview notes is inserted after review (for reviewers separately uploaded on Editorialmanager).

Abolbashari, E.C., Hussain, O.K., Saberi, M. (2018). Smart buyer: a Bayesian network modelling approach for measuring and improving procurement performance in organisations. Knowledge-Based Systems. 142, 127-148. ISSN 0950-7051, 10.1016/j.knosys.2017.11.032.

ACM (2012). ACM Computing Classification System. 7. Association for Computing Machinery. Retrieved from: https://dl.acm.org/ccs (accessed August 6th, 2022).

Allal-Chérif, O., Simón-Moya, V., Carlos Cuenca Ballester, A.C.C. (2021). Intelligent purchasing: how artificial intelligence can redefine the purchasing function. Journal of Business Research. 124 (C), 69-76. ISSN 0148-2963, 10.1016/j.jbusres.2020.11.050.

ASCM (2020). APICS Supply Chain Operations Reference model. 13. Association for Supply Chain Management. Retrieved from: https://www.ascm.org/globalassets/ascm_website_assets/docs/intro-and-front-matter-scor-digital-standard.pdf (accessed September 29th, 2023).

Automated Negotiation SCM Consortium (2023). Overview of Automated Negotiation. Retrieved from: https://automated-negotiation.org/en/automaticnegotiation/ (accessed March 1st, 2023).

Baarslag, T., Kaisers, M., Gerding, E., Jonker, C.M., Gratch, J. (2017). When will negotiation agents be able to represent us? The challenges and opportunities for autonomous negotiators. International Joint Conference on Artificial Intelligence. 26, 4684-4690. 10.24963/ijcai.2017/653.

Bäckstrand, J., Suurmond, R. van Raaij, E., Chen, C. (2019). Purchasing process models: inspiration for teaching purchasing and supply management. Journal of Purchasing and Supply Management. 25 (5). ISSN 1478-4092, 10.1016/j.pursup.2019.100577.

Bals, L., Schulze, H., Kelly, S., Stek, K. Purchasing and supply management (PSM) competencies: Current and future requirements. Journal of Purchasing and Supply Management. 25 (5), 100572. ISSN 1478-4092, 10.1016/j.pursup.2019.100572.

Bienhaus, F. and Haddud, A. (2018). Procurement 4.0: factors influencing the digitisation of procurement and supply chains. Business Process Management Journal. 24 (4), 965-984. ISSN 1463-7154, 10.1108/BPMJ-06-2017-0139.

Bodaghi, G., Jolai, F., Rabbani, M. (2018). An integrated weighted fuzzy multi objective model for supplier selection and order scheduling in a supply chain. International Journal of Production Research. 56 (10), 3590-3614. ISSN 1366-588X, 10.1080/00207543.2017.1400706.

Bodendorf, F., Merkl, P., Franke, J. (2022). Artificial neural networks for intelligent cost estimation - a contribution to strategic cost management in the manufacturing supply chain. International Journal of Production Research. 60 (21), 6637-6658. ISSN 1366-588X, 10.1080/00207543.2021.1998697.

Booth, B. and Sharma, A. (2019). Cognitive procurement: seizing the AI opportunity. IBM. Retrieved from: https://www.ibm.com/downloads/cas/MV6LX6R2 (accessed August 6th, 2022).

Botfriends (2023). Procurement 4.0: fit for the future with digitization and automation. Retrieved from: https://botfriends.de/en/whitepapers/einkauf-4-0/ (accessed October 3rd, 2023).

Brereton, P., Kitchenham, B.A., Budgen, D., Turner, M., Khalil, M. (2007). Lessons from applying the systematic literature review process within the software engineering domain. Journal of Systems and Software. 80 (4), 571-583. ISSN 0164-1212, 10.1016/j.jss.2006.07.009.

Brinch, M. (2018). Understanding the value of big data in supply chain management and its business processes. International Journal of Operations and Production Management. 38 (7), 1589-1614. ISSN 1758-6593, 10.1108/IJOPM-05-2017-0268.

Burger, M, Nitsche, A.M., Arlinghaus, J. (2023). Hybrid intelligence in procurement: disillusionment with AI's superiority? Computers in Industry. 150, 103946. ISSN 0166-3615, 10.1016/j.compind.2023.103946.

Caputo, A.C. and Pelagagge, P.M. (2008). Parametric and neural methods for cost estimation of process vessels. International Journal of Production Economics. 112 (2), 934-954. ISSN 1925-5273, 10.1016/j.ijpe.2007.08.002.

Carbonneau, R.A., Kersten, G.E., Vahidov, R. (2008). Predicting opponent's moves in electronic negotiations using neural networks. Expert Systems with Applications. 34 (2), 1266-1273. ISSN 0957-4174, 10.1016/j.eswa.2006.12.027.

Cavalcante, I., Frazzon, E., Forcellini, F., Ivanov, D. (2019). A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. International Journal of Information Management. 49, 86-97. ISSN 0268-4012, 10.1016/j.ijinfomgt.2019.03.004.

Chehbi-Gamoura, S., Derrouiche, R., Damand, D., Barth, M. (2019). Insights from big data analytics in supply chain management: an all-inclusive literature review using the SCOR model. Production Planning and Control. 31 (5), 1-27. ISSN 0953-7287, 10.1080/09537287.2019.1639839.

Cheung, C.F., Wang, W.M., Lo, V., Lee, W.B. (2004). An agent-oriented and knowledge-based system for strategic e-procurement. Expert Systems with Applications. 21 (1), 11-21. ISSN 0957-4174, 10.1111/j.1468-0394.2004.00259.x.

Choi, Y., Lee, H., Irani, Z. (2018). Big data-driven fuzzy cognitive map for prioritizing IT service procurement in the public sector. Annals of Operations Research. 270 (1-2), 75-104. ISSN 1572-9338, 10.1007/s10479-016-2281-6.

Chou, J.S., Lin, C.W., Pham, A.D., Shao, J.Y. (2015). Optimized artificial intelligence models for predicting project award price. Automation in Construction. 54, 106-115. ISSN 0926-5805, 10.1016/j.autcon.2015.02.006.

Choy, K.L, Lee, W.B., Lo, V. (2002). An intelligent supplier management tool for benchmarking suppliers in outsource manufacturing. Expert Systems with Applications. 22 (3), 213-224. ISSN 0957-4174, 10.1016/S0957-4174(01)00055-0.

Choy, K.L, Lee, W.B., Lo, V. (2003). Design of an intelligent supplier relationship management system: a hybrid case based neural network approach. Expert Systems with Applications. 24 (2), 225-237. ISSN 0957-4174, 10.1016/S0957-4174(02)00151-3.

Chui, M., Hall, B., Meyhem, H., Singla, A. (2022). The state of AI in 2022 - and a half decade in review. McKinsey. 5. Retrieved from: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2022-and-a-half-decade-in-review (accessed January 19th, 2023).

Cui, R., Li, M., Zhang, S. (2022a). AI and procurement. Manufacturing and Service Operations Management. 24 (2), 691-706. ISSN 1526-5498, 10.1287/msom.2021.0989.

Cui, Z., Li, X., Robotis, A., Batsakis, G., Braganza, A. (2022b). An interdisciplinary systematic review on artificial intelligence in management and technology. Academy of Management Proceedings. 82. 10.5465/AMBPP.2022.17577abstract.

Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly. 13 (3), 319-340. ISSN 2162-9730, 10.2307/249008.

Degraeve, Z., Labro, E., Roodhooft, F. (2004). Total cost of ownership purchasing of a service: the case of airline selection at Alcatel Bell. European Journal of Operational Research. 156 (1), 23-40. ISSN 0377-2217, 10.1016/j.ejor.2003.08.002.

Deloitte (2020). Study on up-take of emerging technologies in public procurement. Retrieved from: https://ec.europa.eu/isa2/news/emerging-technologies-public-procurement-study-results_en/ (accessed November 13th, 2022).

Dietvorst, B.J., Simmons, J.P., Massey, C. (2018). Overcoming algorithm aversion: people will use imperfect algorithms if they can (even slightly) modify them. Management Science. 64 (3), 1155-1170. ISSN 1526-5501, 10.1287/mnsc.2016.2643.

Durach, C.F., Kembro, J., Wieland, A. (2017). A new paradigm for systematic literature reviews in supply chain management. Journal of Supply Chain Management. 53 (4), 67-85. ISSN 1745-493X, 10.1111/jscm.12145.

Durach, C.F., Kembro, J., Wieland, A. (2021). How to advance theory through literature reviews in logistics and supply chain management. International Journal of Physical Distribution and Logistics Management. 51 (10), 1090-1107, ISSN 0960-003510.1108/IJPDLM-11-2020-0381.

Faez, F., Ghodsypour, S.H., O'Brien, C. (2009). Vendor selection and order allocation using an integrated fuzzy case-based reasoning and mathematical programming model. International Journal of Production Economics. 121 (2), 395-408. ISSN 0925-5273, 10.1016/j.ijpe.2006.11.022.

Ferreira, L. and Borenstein, D. (2012). A fuzzy-Bayesian model for supplier selection. Expert Systems with Applications. 39 (9), 7834-7844. ISSN 0957-4174, 10.1016/j.eswa.2012.01.068.

Flechsig, C., Anslinger, F., Lasch, R. (2022). Robotic Process Automation in purchasing and supply management: A multiple case study on potentials, barriers, and implementation. Journal of Purchasing and Supply Management. 28 (1), 100718. ISSN 1478-4092, 10.1016/j.pursup.2021.100718.

Frolov, D., Nascimento, S., Fenner, T., Mirkin, B. (2020). Parsimonious generalization of fuzzy thematic sets in taxonomies applied to the analysis of tendencies of research in data science. Information Sciences. 512, 595-615. ISSN 0020-0255, 10.1016/j.ins.2019.09.082.

Gartner (2018). Analytics. Retrieved from: https://www.gartner.com/en/information-technology/glossary/analytics (accessed July 16th, 2022).

Gratch, J. (2021). The Promise and Peril of Automated Negotiators. Negotiation Journal. 37, 13-34. ISSN 1571-9979, 10.1111/nejo.12348.

Gräve, P. (2021). Porsche, Audi and Volkswagen use artificial intelligence to minimise sustainability risks. Porsche Newsroom. Retrieved from: https://newsroom.porsche.com/en/2021/sustainability/porsche-audi-volkswagen-pilot-project-artificial-intelligence-minimisation-sustainability-risks-supply-chain-23801.html (retrieved November 13th, 2022).

Guida, M., Caniato, F., Moretto, A., Ronchi, S. (2023). The role of artificial intelligence in the procurement process: state of the art and research agenda. Journal of Purchasing and Supply Management. 100823. ISSN 1478-4092, 10.1016/j.pursup.2023.100823.

Gunasekaran, A., Papadopoulos, T. Dubey, R., Wamba, S.F., Childe, S.J., Hazen, B.T., Akter, B.S. (2017). Big data and predictive analytics for supply chain and organizational performance. Journal of Business Research. 70, 308-317. ISSN 0148-2963, 10.1016/j.jbusres.2016.08.004.

Guo, X., Yuan, Z., Tian, B. (2009). Supplier selection based on hierarchical potential support vector machine. Expert Systems with Applications. 36 (2), 6978-6985. ISSN 0957-4174, 10.1016/j.eswa.2008.08.074.

Guosheng, H. and Guohong, Z. (2008). Comparison on neural networks and support vector machines in suppliers' selection. Journal of Systems Engineering and Electronics. 19 (2), 316-320. ISSN 1671-1793, 10.1016/S1004-4132(08)60085-7.

Handfield, R.B., Jeong, S., Choi, T.Y. (2019). Emerging procurement technology: data analytics and cognitive analytics. International Journal of Physical Distribution and Logistics Management. 49 (10), 972-1002. ISSN 0960-0035, 10.1108/IJPDLM-11-2017-0348.

Herold, S., Heller, J., Rozemeijer, F., Mahr, D. (2022). Dynamic capabilities for digital procurement transformation: a systematic literature review. International Journal of Physical Distribution and Logistics Management. ISSN 0960-0035, 10.1108/IJPDLM-12-2021-0535.

Hindriks, K. and Tykhonov, D. (2008). Opponent modelling in automated multi-issue negotiation using Bayesian learning. International Joint Conference on Autonomous Agents and Multiagent System. 1, 331-338. 10.5555/1402383.1402433.

Hofmann, M., Neukart, F., Bäck, T. (2017). Artificial intelligence and data science in the automotive industry. ArXiv. 10.48550/arXiv.1709.01989.

Hosseini, S. and Barker, K. (2016). A Bayesian network model for resilience-based supplier selection. International Journal of Production Economics. 180 (C), 68-87. ISSN 1925-5273 10.1016/j.ijpe.2016.07.007.

Hülsbömer, D. (2019). IAA buyers' day: staying mobile in purchasing. German Association Materials Management, Purchasing and Logistics BME. Retrieved from: https://www.bmeopensourcing.com/en/blog/iaa-buyers-day-staying-mobile-in-purchasing/ (accessed August 28th, 2022).

Jain, R., Singh, A.R., Yadav, H.C., Mishra, P. (2014). Using data mining synergies for evaluating criteria at pre-qualification stage of supplier selection. Journal of Intelligent Manufacturing. 25 (1), 165-175. ISSN 1467-8691, 10.1007/s10845-012-0684-z.

Jordon, K., Dossou, P.E., Junior, J.C. (2019). Using lean manufacturing and machine learning for improving medicines procurement and dispatching in a hospital. Procedia Manufacturing. 38, 1034-1041. ISSN 2351-9789, 10.1016/j.promfg.2020.01.189.

Kahn, J. (2021). This A.I. startup is saving Walmart and other big companies millions by automating negotiations. Forbes. Retrieved from: https://fortune.com/2021/04/27/a-i-startup-pactum-negotiating-software-saving-walmart-money/ (accessed November 13th, 2022).

Kang, H.Y., Lee, A.H.I., Yang, C.Y. (2012). A fuzzy ANP model for supplier selection as applied to IC packaging. Journal of Intelligent Manufacturing. 23, 1477-1488. ISSN 0956-5515, 10.1007/s10845-010-0448-6.

Kashiwagi, D. and Byfield, R. (2002). Testing of minimization of subjectivity in best value procurement by using artificial intelligence systems in State of Utah procurement. Journal of Construction Engineering and Management. 128 (6). ISSN 0733-9364, 10.1061/(ASCE)0733-9364(2002)128:6(496).

Khoo, L.P., Tor, S., Lee, S. (1998). The potential of intelligent software agents in the World Wide Web in automating part procurement. Journal of Supply Chain Management. 34 (4), 46-52. ISSN 1745-493X, 10.1111/j.1745-493X.1998.tb00041.x.

Knight, L., Tate, W., Carnovale, S., Di Mauro, C., Bals, L., Caniato, F., Gualandris, J., Johnsen, T., Matopoulos, A., Meehan, J., Miemczyk, J., Patrucco, A.S, Schoenherr, T., Selviaridis, K., Touboulic, A., Wagner, S.M. (2022). Future business and the role of purchasing and supply management: opportunities for 'business-not-as-usual' PSM research. Journal of Purchasing and Supply Management. 28 (1). ISSN 1478-4092, 10.1016/j.pursup.2022.100753.

Kuo, R.J., Wang, Y.C., Tien, F.C. (2010). Integration of artificial neural network and MADA methods for green supplier selection. Journal of Cleaner Production. 18 (12), 1161-1170. ISSN 0959-6526, 10.1016/j.jclepro.2010.03.020.

Lam, K.C., Hu, T., Ng, S.T., Skitmore, M., Cheung, S.O. (2001). A fuzzy neural network approach for contractor prequalification. Construction Management and Economics. 19 (2), 175-188. ISSN 1466-433X, 10.1080/01446190150505108.

Lee, C.C. and Ou-Yang, C. (2009). A neural networks approach for forecasting the supplier's bid prices in supplier selection negotiation process. Expert Systems with Applications. 36 (2), 2961-2970. ISSN 0957-4174, 10.1016/j.eswa.2008.01.063.

Li, B.H., Hou, B., Yu, W. (2017). Applications of artificial intelligence in intelligent manufacturing: a review. Frontiers Information Technology Electronic Engineering. 18 (1), 86-96. ISSN 2095-9230, 10.1631/FITEE.1601885.

Lin, C.C., Chen, S.C., Chu, Y.M. (2011). Automatic price negotiation on the web: an agent-based web application using fuzzy expert system. Expert Systems with Applications. 38 (5), 5090-5100. ISSN 0957-4174, 10.1016/j.eswa.2010.09.142.

Lindsey, S. (2020). How AI and analytics are transforming procurement. Amazon. Retrieved from: https://business.amazon.com/en/discover-more/blog/how-ai-and-ml-are-transforming-procurement (accessed August 6th, 2022).

Luan, J., Yao, Z., Zhao, F., Song, X. (2019). A novel method to solve supplier selection problem: hybrid algorithm of genetic algorithm and ant colony optimization. Mathematics and Computers in Simulation. 156, 294-309. ISSN 0378-4754, 10.1016/j.matcom.2018.08.011.

Marlinghaus, S. (2018). Interview: traditional procurement, in many cases, will not survive. Roland Berger. Retrieved from: https://www.rolandberger.com/en/Insights/Publications/Interview-Traditional-Procurement-In-many-cases-will-not-survive.html (accessed November 13th, 2022).

Matwin, S., Szpakowicz, S., Koperczak, Z., Kersten, G.E., Michalowski, W. (1989). Negoplan: an expert system shell for negotiation support. IEEE Intelligent Systems. 4 (4), 50-62. ISSN 1541-1672, 10.1109/64.43285.

Mayring, P. (2014). Qualitative content analysis - theoretical foundation, basic procedures and software solution. Retrieved from https://www.ssoar.info/ssoar/handle/document/39517 (accessed July 16th, 2022).

McCracken, G. (1988). The long interview. Sage Publications. 13. ISBN 978-1412986229.

Mell, J., Lucas, G., Mozgai, S., Gratch, J. (2020). The effects of experience on deception in human-agent negotiation. Journal of Artificial Intelligence Research. 68, 633-660. ISSN 1076-9757, 10.1613/jair.1.11924.

Meyer, D. and Henke, M. (2023). Developing design principles for the implementation of AI in PSM: An investigation with expert interviews. Journal of Purchasing and Supply Management. 100846. ISSN 1478-4092, 10.1016/j.pursup.2023.100846.

Mittal, N., Saif, R., Ammanath, B. (2022). Fueling the AI transformation: four key actions powering widespread value from AI, right now. Deloitte. 5. Retrieved from: https://www2.deloitte.com/us/en/pages/consulting/articles/state-of-ai-2022.html (accessed November 13th, 2022).

Moghadam, M.R.S., Afsar, A., Sohrabi, B. (2008). Inventory lot-sizing with supplier selection using hybrid intelligent algorithm. Applied Soft Computing. 8 (4), 1523-1529. ISSN 1568-4946, 10.1016/j.asoc.2007.11.001.

Moosmayer, D.C., Chong, A.Y.L., Liu, M.J., Schuppar, B. (2013). A neural network approach to predicting price negotiation outcomes in business-to-business contexts. Expert Systems with Applications. 40 (8), 3028-3035. ISSN 0957-4174, 10.1016/j.eswa.2012.12.018.

Murfield, M.L.U., Ellram, L.M., Giunipero, L.C. (2021). Evaluating the identity of purchasing and supply management: roadblocks to moving beyond a cost-focused identity. Journal of Purchasing and Supply Management. 100687. ISSN 1478-4092, 10.1016/j.pursup.2021.100687.

Murray, B. (2022). Pactum Raises $20 Million in Maersk-Backed Funding to Grow AI Deal-Making. Bloomberg. Retrieved from: https://www.bloomberg.com/news/newsletters/2022-12-08/supply-chain-latest-pactum-automates-supplier-negotiations (accessed February 27th, 2023).

Narasimhan, R., Talluri, S., Mendez, D. (2001). Supplier evaluation and rationalization via data envelopment analysis. Journal of Supply Chain Management. 37 (2), 28-37. ISSN 1745-493X, 10.1111/j.1745-493X.2001.tb00103.x.

Nepal, B. and Yadav, O.P. (2015). Bayesian belief network-based framework for sourcing risk analysis during supplier selection. International Journal of Production Research. 53 (20), 1-22. ISSN 1366-588X, 10.1080/00207543.2015.1027011.

Ng, A. (2019). How to choose your first AI project. Harvard Business Review. 2. Retrieved from: https://hbr.org/2019/02/how-to-choose-your-first-ai-project (accessed December 8th, 2022).

Nguyen, T., Zhou, L., Spiegler, V., Leromonachou, P., Lin, Y. (2018). Big data analytics in supply chain management: a state-of-the-art literature review. Computers and Operations Research. 98, 254-264. ISSN 0305-0548, 10.1016/j.cor.2017.07.004.

Ni, D., Xiao, Z., Lim, M.K. (2020). A systematic review of the research trends of machine learning in supply chain management. International Journal of Machine Learning and Cybernetics. 11 (7), 1463-1482. ISSN 1868-808X, 10.1007/s13042-019-01050-0.

Nitsche, A.M., Burger, M., Arlinghaus, J., Schumann, C.A., Franczyk, B. (2021a). Smarter relationships? The present and future scope of AI application in buyer-supplier relationships. International Conference on Computational Logistics. 12, 237-251. 10.1007/978-3-030-87672-2_16.

Nitsche, A.M., Schumann, C.A., Franczyk, B., Reuther, K. (2021b). Artificial intelligence inspired supply chain collaboration: a design-science research and system dynamics approach. IEEE International Conference on Engineering, Technology and Innovation. 27, 1-9. 10.1109/ICE/ITMC52061.2021.9570266.

Oliver, J. (1996). Machine-learning approach to automated negotiation and prospects for electronic commerce. Journal of Management Information Systems. 13 (3), 83-112. ISSN 1557928X, 10.1080/07421222.1996.11518135.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. The BMJ. 372 (71). ISSN 1756-1833, 10.1136/bmj.n71.

Pagliari, C., Sloan, D., Gregor, P., Sullivan, F., Detmer, D., Kahan, J., Oortwijn, W., MacGillivray, S. (2005). What is eHealth (4): a scoping exercise to map the field. Journal of Medical Internet Research. 7 (1), 68-86. ISSN 1438-8871, 10.2196/jmir.7.1.e9.

Papa, T., Kaufman, A., Maxwell, C. (2019). Procurement at half the cost: when bots do the buying. Accenture Strategy. 1 (8). Retrieved from: https://www.accenture.com/t20170409t223246__w__/us-en/_acnmedia/pdf-48/accenture-when-bots-do-the-buying-pov.pdf (accessed October 3rd, 2023).

Park, D.H., Kim, H.K., Choi, I.Y., Kim, J.K. (2011). A literature review and classification of recommender systems on academic journals. Journal of Intelligence and Information Systems. 17 (1), 10059-10072. ISSN 2288-4882, 10.13088/jiis.2011.17.1.139.

Plebankiewicz, E. (2009). Contractor prequalification model using fuzzy sets. Journal of Civil Engineering and Management. 15 (4), 377-385. ISSN 1822-3605, 10.3846/1392-3730.2009.15.377-385.

Pournader, M., Kach, A., Fahimnia, B., Sarkis, J. (2019). Outsourcing performance quality assessment using data envelopment analytics. International Journal of Production Economics. 207 (C), 173-182. ISSN 0925-5273, 10.1016/j.ijpe.2016.07.004.

Pratt, M., Rockmann, K., Kaufmann, J. (2006). Constructing professional identity: the role of work and identity learning cycles in the customization of identity among medical students. Academy of Management Journal. 49, 235-262. ISSN 1948-0989, 10.5465/AMJ.2006.20786060.

Qi, G.J. and Luo, J. (2020). Small data challenges in big data era: a survey of recent progress on unsupervised and semi-supervised methods. IEEE Transactions on Pattern Analysis and Machine Intelligence. 44 (4), 2168-2187. ISSN 1939-3539, 10.1109/TPAMI.2020.3031898.

Raisch, S. and Krakowski, S. (2021). Artificial intelligence and management: the automation-augmentation paradox. Academy of Management Review. 46 (1), 192-210. ISSN 1930-3807, 10.5465/2018.0072.

Russell, S. and Norvig, P. (2020). Artificial intelligence: a modern approach. Prentice Hall. 4. ISBN 978-0134610993.

Saenz, M.J., Revilla, E., Borella, I. (2022). Digital transformation is changing supply chain relationships. Harvard Business Review. 7. Retrieved from: https://hbr.org/2022/07/digital-transformation-is-changing-supply-chain-relationships (accessed November 21st, 2022).

Sammalkorpi, S. and Teppala, J.P. (2022). AI in procurement. Sievo. Retrieved from: https://sievo.com/resources/ai-in-procurement (accessed May 7th, 2022).

INTERNAL

Schoenherr, T. and Tummala, V.M.R. (2007). Electronic procurement: a structured literature review and directions for future research. International Journal of Procurement Management. 1 (1/2), 8-37. ISSN 1753-8440, 10.1504/IJPM.2007.015353.

Schuh, C., Schnellbacher, W., Triplat, A., Weise, D. (2022). Profit from the source: transforming your business by putting suppliers at the core. Harvard Business Press Review. 1. ISBN 978-1647821395.

Schulze-Horn, I., Hueren, S., Scheffler, P., Schiele, H. (2020). Artificial intelligence in purchasing: facilitating mechanism design-based negotiations. Applied Artificial Intelligence. 34 (8), 618-642. ISSN 1087-6545, 10.1080/08839514.2020.1749337.

Seuring, S. and Gold, S. (2012). Conducting content-analysis based literature reviews in supply chain management. Supply Chain Management: An International Journal. 17 (5), 544-555. ISSN 1359-8546, 10.1108/13598541211258609.

Seyedan, M. and Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities. Journal of Big Data. 7 (1). ISSN 2196-1115, 10.1186/s40537-020-00329-2.

Seyedghorban, Z., Samson, D., Tahernejad, H. (2020). Digitalization opportunities for the procurement function: pathways to maturity. International Journal of Operations and Production Management. 40 (11), 1685-1693. ISSN 0144-3577, 10.1108/IJOPM-04-2020-0214.

Shore, B. and Venkatachalam, A.R. (2003). Evaluating the information sharing capabilities of supply chain partners: a fuzzy logic model. International Journal of Physical Distribution and Logistics Management. 33 (9), 804-824. ISSN 0960-0035, 10.1108/09600030310503343.

Sim, K.M., Guo, Y., Shi, B. (2009). BLGAN: Bayesian learning and genetic algorithm for supporting negotiation with incomplete information. IEEE Transactions on Systems, Man, and Cybernetics. 39 (1), 198-211. ISSN 2168-2216, 10.1109/TSMCB.2008.2004501.

Simsek, Z., Bansal, P.T., Shaw, J.D., Heugens, P., Smith, W. K. (2018). From the Editors - Seeing Practice Impact in New Ways. Academy of Management Journal. 61, 2021-2025. ISSN 0001-4273. 10.5465/amj.2018.4006.

Spina, G., Caniato, F., Luzzini, D., Ronchi, S. (2016). Past, present and future trends of purchasing and supply management: an extensive literature review. Industrial Marketing Management. 42 (8), 1202-1212. ISSN 0019-8501, 10.1016/j.indmarman.2013.04.001.

Spreitzenbarth, J.M. and Stuckenschmidt, H. (2021). Supplier selection with AI-based TCO models: cost prediction case study in an automotive OEM. American Association of Cost Engineers International Conference and Expo. 30. Retrieved from: https://web.aacei.org/docs/default-source/annual-conference/2021-aace-conex---technical-sessions.pdf?sfvrsn=22 (accessed November 13th, 2022).

Spreitzenbarth, J.M., Stuckenschmidt, H., Bode, C. (2022). The state of artificial intelligence: procurement vs sales and marketing. In: Bode, C., Bogaschewsky, R., Eßig, M., Lasch, R., Stötzle, W. (editors). Supply Management Research: Advanced Studies in Supply Management. Springer. 15 (1), 173-193. ISSN 2626-2150, 10.1007/978-3-658-38350-3_8.

Spreitzenbarth, J.M., Stuckenschmidt, H., Bode, C. (2024). Designing an AI purchasing requisition bundling generator. Computers in Industry. 155, 104043. ISSN 0166-3615, 10.1016/j.compind.2023.104043.

Straub, S. (2019). How sourcing bots automate 93% of tasks in ocean mini-tenders. Keelvar. Retrieved from: https://www.keelvar.com/blog/sourcing-bot-automation-keelvar (accessed August 6th, 2022).

Suurmond, R., Wynstra, F., Vermeij, A., Haag, E.J. (2023). Note and Debate: Text mining and network analytics for literature reviews: Exploring the landscape of purchasing and supply management research. Journal of Purchasing and Supply Management. 100892. ISSN 1478-4092, 10.1016/j.pursup.2023.100892.

Tata Consultancy Services (2016). Getting smarter by the day: how artificial intelligence is elevating the performance of global companies. Retrieved from: https://brasscom.org.br/wp-content/uploads/2018/01/TSC-PPT-TCS-Global-Trend-Study-AI-Overview-for-MKT-Comm.pdf (accessed October 3rd, 2023).

Tate, W., Ellram, L.M., Bals, L. (2022). A handbook of theories for purchasing, supply chain and management research. Edward Elgar Publishing Limited. 1. ISBN 978-1839104497.

Teece, D.J., Pisano, G., Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal. 18, 509-533. ISSN 1097-0266, 10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z.

Thomé, A.M., Scavarda, L.F., Scavarda, A.J. (2016). Conducting systematic literature reviews in operations management. Production Planning and Control. 27 (5), 408-420. ISSN 0953-7287, 10.1080/09537287.2015.1129464.

Tranfield, D., Denyer, D., Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. British Journal of Management. 14. 207-222. ISSN 1467-8551, 10.1111/1467-8551.00375.

United Nations (2008). International Standard Industrial Classification of All Economic Activities (ISIC). 4. ISBN 978-9211615180. Retrieved from: https://unstats.un.org/unsd/publication/seriesm/seriesm_4rev4e.pdf (accessed July 16th, 2022).

Vahdani, B., Iranmanesh, S.H., Meysam Mousavi, S., Abdollahzade, M. (2012). A locally linear neuro-fuzzy model for supplier selection in cosmetics industry. Applied Mathematical Modelling. 36 (10), 4714-4727. ISSN 0307-904X, 10.1016/j.apm.2011.12.006.

van Weele, A.J. (2018). Purchasing and supply chain management. Cengage Learning. 7. ISBN 978-1473749443.

Veit, F., Geyer-Klingeberg, J., Madrzak, J., Haug, M., Thomson, J. (2017). The proactive insights engine: process mining meets machine learning and artificial intelligence. International Conference on Business Process Management. 15.

Venkatesh, V.G., Zhang, A., Deakins, E., Luthra, S., Mangla, S. (2019). A fuzzy AHP-TOPSIS approach to supply partner selection in continuous aid humanitarian supply chains. Annals of Operations Research. 283 (1), 1517-1550. ISSN 1572-9338, 10.1007/s10479-018-2981-1.

Vollmer, M., Brimm, R., Eberhard, M. (2018). Procurement 2025: an SAP perspective. Retrieved from: https://apollogic.com/wp-content/uploads/2018/10/SAP-Ariba-Report-Procurement-2025.pdf (accessed October 3rd, 2023).

Wamba, S.F., Queiroz, M.M., Guthrie, C., Braganza, A. (2021). Industry experiences of artificial intelligence (AI): benefits and challenges in operations and supply chain management. Production Planning and Control. 33 (16), 1493-1497. ISSN 0953-7287, 10.1080/09537287.2021.1882695.

World Economic Forum (2019). Guidelines for AI procurement. Retrieved from: https://www.weforum.org/whitepapers/ai-government-procurement-guidelines/ (accessed October 30th, 2022).

Woschank, M., Rauch, E., Zsifkovits, H. (2020). A review of further directions for artificial intelligence, machine learning, and deep learning in smart logistics. Sustainability. 12 (9). ISSN 2071-1050, 10.3390/su12093760.

Wu, C. and Barnes, D. (2012). A dynamic feedback model for partner selection in agile supply chains. International Journal of Operations and Production Management. 32 (1), 79-103. ISSN 0144-3577, 10.1108/01443561211195745.

Wu, C. and Barnes, D. (2016). Partner selection for reverse logistics centres in green supply chains: a fuzzy artificial immune optimisation approach. Production Planning and Control. 27 (16), 1356-1372. ISSN 0953-7287, 10.1080/09537287.2016.1221159.

Wynstra, F., Suurmond, R., Nullmeier, F. (2019). Purchasing and supply management as a multidisciplinary research field: unity in diversity? Journal of Purchasing and Supply Management. 25 (5). ISSN 1478-4092, 10.1016/j.pursup.2019.100578.

Yücenur, G.N., Vayvay, Ö., Demirel, N.C. (2011). Supplier selection problem in global supply chains by AHP and ANP approaches under fuzzy environment. International Journal of Advanced Manufacturing Technology. 56 (5-8), 823-833. ISSN 1433-3015, 10.1007/s00170-011-3220-y.

Ziegler, M., Rossmann, S., Steer, A., Danzer, S. (2019). Leading the way to an AI-driven organization. Porsche Consulting. Retrieved from: https://newsroom.porsche.com/en/2019/company/porsche-consulting-study-ai-driven-organization-19309.html (accessed September 29th, 2023).

Appendices

A. Semi-structured interview guideline

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?

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 2 in the section on triangulating results.

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

37

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

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 2

B. List of expert interviews

Table B.1.
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

38

Highlights

- 46 works of AI and ML in PSM were iteratively classified in 11 use case clusters
- Content analysis method was extended by interviews to enrich material evaluation
- The Computer Classification System was utilized as clearly defined taxonomy
- Identified a mismatch between current research focus and practitioners' assessment
- Cost analysis deserves higher attention and the operational area of procurement

Author biographies

Jan Martin Spreitzenbarth is an external doctoral student at the Endowed Chair of Procurement at the University of Mannheim in Germany. His research interests lie at the application of artificial intelligence and machine learning in purchasing and supply management. He received his master's degree in Production and Operations Management from Karlsruhe Institute of Technology in Germany and his bachelor's degree from Simpson College in the United States of America. Jan works in the smart mobility procurement unit of Porsche and is currently assigned to the build-up of the newly founded CARIAD bundling the software competencies worldwide within the Volkswagen Group.
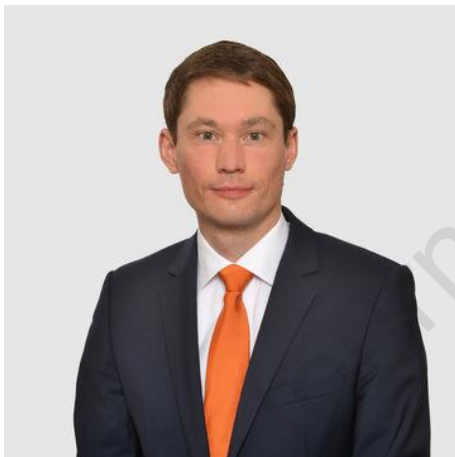
Christoph Bode is a full professor at the Business School of the University of Mannheim and holds the Endowed Chair of Procurement. His teaching and research interests lie in the areas of procurement, supply chain, logistics, and operations management with a special focus on risk and disruptions, interfirm relationships, innovation and entrepreneurship, sustainability as well as strategies and performance.

Heiner Stuckenschmidt is a full professor of Computer Science and chair holder for Artificial Intelligence at the University of Mannheim. Heiner's group performs fundamental and applied research in knowledge representation and reasoning with a focus on combining logical and probabilistic reasoning. His recent interests include the application of supervised and unsupervised methods to the problem of human activity recognition.