# ARTIFICIAL INTELLIGENCE (AI) IN E-PROCUREMENT: A LITERATURE REVIEW

Harald Konnerth

Upper Austria University of Applied Sciences, Wehrgrabengasse 3, Steyr 4400, Austria

**Abstract**

*The goal of e-procurement is to ensure the availability of relevant goods in a company, services, and other resources. A distinction is made between the strategic goals, which include quality and supply assurance, and the operational goals such as reduction of storage costs and optimization of the costs of activities in the ordering process. Despite the complexity and potential of E-procurement, support by artificial intelligence (AI) is still not widespread. To capture the current state of research and its use in practice, a systematic literature review on the use of AI in e-procurement is conducted in this paper.*

**Keywords:** *E-Procurement, Artificial Intelligence, Machine Learning, Digitalization*

## 1. INTRODUCTION

The term e-procurement refers to the electronic purchasing of goods and services by a company with the aid of internet technologies. It is to be completed with the electronic purchase of the procedures relevant to the procurement of an enterprise and its suppliers. Purchasing is an essential part of the corporate strategy, since more than half of the effort is caused by purchasing (Bienhaus and Haddud, 2018). Procurement can also represent a competitive advantage for a company if an increase in the quality of merchandise can be achieved through procurement (Schütz et al., 2019). Procurement departments usually work in a highly structured manner and process large amounts of data, so the use of artificial intelligence (AI) can bring about an improvement in the procurement process and thus represent an additional process improvement. The procurement process is usually not yet the focus for research into the use of AI, but so far, the goal has mostly been sales and marketing (Tirunillai and Tellis, 2014) and risk management (Baryannis et al., 2019).

Artificial intelligence (AI) refers to the ability of machines and computer systems to perform tasks that would normally require human thought. The main goal of AI is to endow machines with "intelligent" behavior so that they can analyze data, recognize patterns, solve problems, make decisions, and even develop human-like cognitive abilities (Bawack et al., 2019).

There are several types of AI, and they can be divided into two main categories (Corea and Coreo, 2019):

1. weak artificial intelligence so-called narrow AI: This form of AI is specialized in a specific task or domain. It can perform that task well, but it does not have general intelligence. Instances of narrow AI encompass virtual assistants like Apple's Siri or Amazon's Alexa, which rely on voice recognition and processing to fulfill specific inquiries or execute designated actions.

2. strong artificial intelligence (so-called general AI): This type of AI is designed to achieve general cognitive function similar to human intelligence. The idea behind strong AI is that it should be able to handle a variety of tasks and learn flexibly, much like a human. Strong AI is currently hypothetical and does not yet exist in reality.

To what extent AI is already used to support e-procurement will be explored in the current literature review, that the potential of AI remains untapped in many procurement activities (Wang et al., 2016). The paper aims the current support of AI in the procurement process.

This paper is structured as follows: Firstly, the methodology of the review in chapter 2. Chapter 3 deals with the analysis in which the answers to the research questions and issues are discussed. Chapter 4 provides a discussion of the results.

## 2. MATERIALS AND METHODS

*2.1. Methods*

This paper undertakes a systematic literature review (SLR) to explore the potential applications of AI in e-procurement. Systematic literature reviews using the PRISMA method involve systematically searching for articles on a particular topic in various library databases or other sources, reviewing the articles for relevance, and further evaluating the full-text articles for consequently both qualitative and quantitative analyses are conducted. (Pickering and Byrne, 2014).

The PRISMA method utilizes systematic methodologies to identify, select, and evaluate relevant research, while also collecting and analyzing data from the chosen studies, aiming to provide a comprehensive and reproducible review. (Pickering and Byrne, 2014). The methodology is allowed in natural and social sciences and information systems (Wimmer et al., 2017).

*2.1.1. Search Query*

To identify papers for e-procurement, the following library databases (ACM, EBSCO, IEEE, Scholar) were searched for articles for the last 5 years with a starting date of 1/1/2018 using the following search query: ("e-procurement" OR "procurement") AND ("artificial intelligence" OR "machine learning").

*2.1.2 Research Questions*

When conducting the systematic literature review (SLR), three main research questions were defined. To answer each of these questions, relevant articles from the retrieved articles were identified, examined, and thoroughly analyzed. The research questions are as follows:

RQ1: Which parts of the purchasing process are supported by AI-based functions?

RQ2: Which goals are pursued through the use of AI?

RQ3: Which technology, technique or method is used?

*2.1.3 Inclusion/Exclusion Criteria*

The subsequent set of inclusion and exclusion criteria was applied:

Criterion 1: Papers published within the last 5 years from Jan 1, 2018, were accepted.

Criterion 2: Only papers in English were used.

Criterion 3: Literature reviews, comparative studies, surveys, feasibility studies, and secondary studies were not considered as secondary studies generally do not provide new research findings.

*2.1.4 Quality evaluation*

The papers to be considered were selected from the point of view of the following quality evaluation criteria. Three questions were defined. These questions include rigor, significance, validity, and reliability. For each criterion, the paper received one point. To be included in the selection, at least two points had to be achieved.

- Does the paper contain a clear statement of the research objective?

- Is there a discussion of the results?

*2.1.5 Data Collection*

The study follows the SLR methodology, which provides a clear set of inclusion and exclusion criteria for selecting relevant articles.

First, a review based on the metadata was conducted, followed by a review based on the title, then the abstract was evaluated, and in the last step, the full text was evaluated. In each step, articles that did not fit the inclusion criteria were eliminated. Duplicate papers were also removed, leaving 30 papers at the end of the selection process.

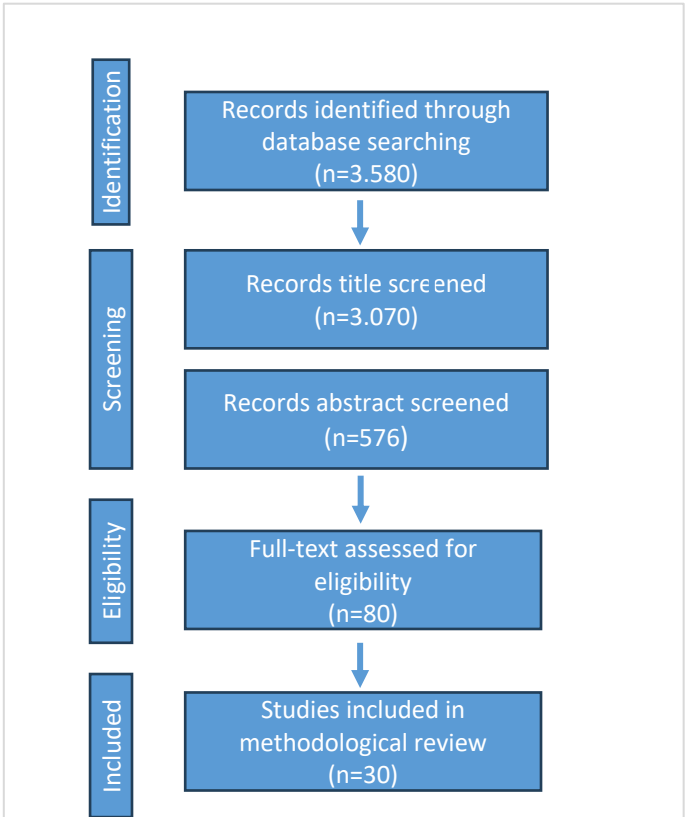


**Fig. 1.** Selection Process

*2.1.6 Findings*

This chapter presents the findings, starting with the initial search results:

| **Database** | **ACM** | **EBSCO** | **IEEE** | **Google Scholar** |
|---|---|---|---|---|
| **Number of publications** | 1.714 | 500 | 2.878 | 3.580 |

**Table 1.** Initial Results

The number of articles found was still extensive in the first step. Table 1 shows the number of articles analyzed.

By implementing the exclusion criteria and evaluating the titles and abstracts, the articles were reduced to the following number.

| **Database** | **ACM** | **EBSCO** | **IEEE** | **Google Scholar** |
|---|---|---|---|---|
| **Number of publications** | 39 | 38 | 44 | 80 |

**Table 2.** Distribution of Analyzed Papers

Below are the outcomes of this final step:

| **Database** | **ACM** | **EBSCO** | **IEEE** | **Google Scholar** |
|---|---|---|---|---|
| **Number of publications** | 7 | 5 | 7 | 11 |

**Table 3.** Included Results After Analysis

*2.1.7 Frequently Used Keywords*

The principal keywords utilized in the research papers are outlined in Fig. 2:

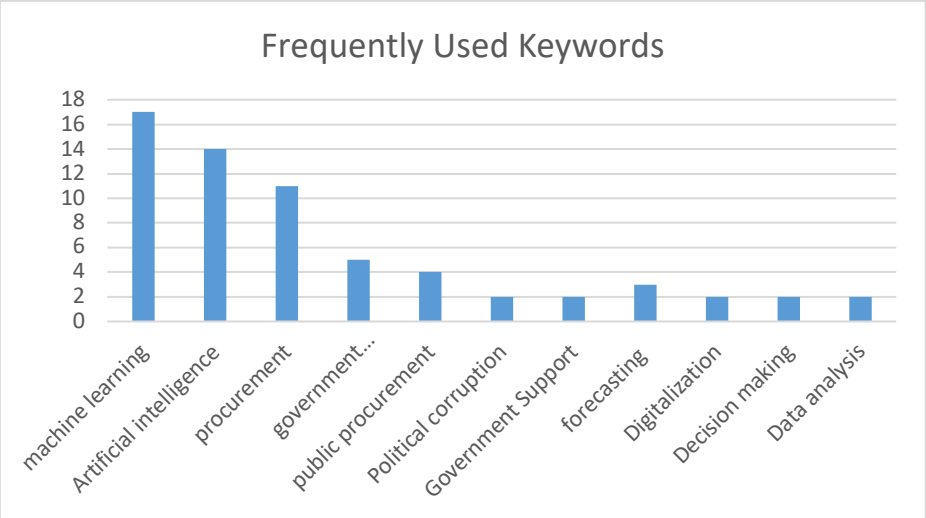


**Fig. 2.** Frequently used Keywords

*2.1.8 Research Papers by Year*

The figure illustrates the annual publication count for the past 5 years, from January 1, 2018.

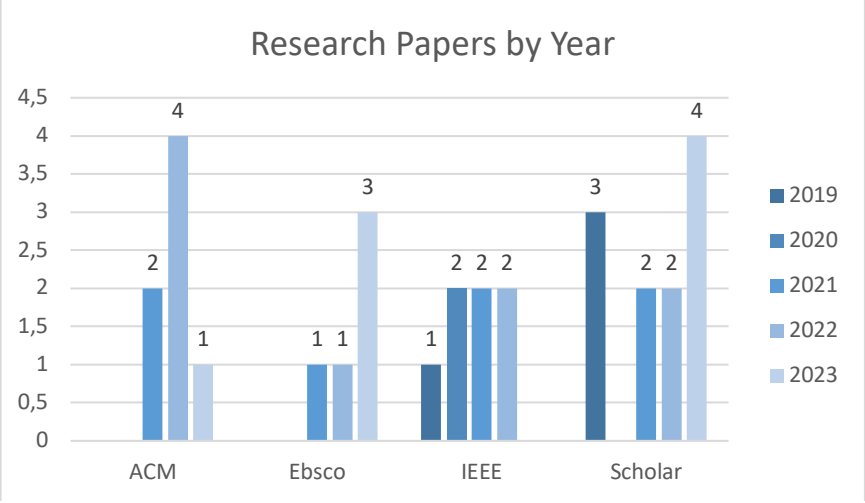


**Fig. 3.** Research Papers by Year

## 3. RESULTS

This chapter provides an analysis of the three research questions previously defined in section 2.1.2.

*3.1. RQ1: Which parts of the purchasing process are supported by AI-based functions?*

The paper Impedovo et al., 2023 mentions the use of Intelligent Robotic Process Automation based on Machine Learning for automating the task of supplier document management in e-procurement platforms. This suggests that AI-based functions support the supplier evaluation part of the purchasing process, which involves managing and evaluating information from documents exchanged through e-procurement platforms.

In the paper Chuang et al., 2021 supports AI the demand forecasting part of the purchasing process. It helps in predicting the future demand for products, which is crucial for inventory management and procurement planning.

The use of a data-driven approach (DDA) for commodity procurement under price is discussed in Mandl & Minner, 2020. This approach supports the decision-making part of the purchasing process, particularly in situations involving forward and spot purchase options under price uncertainty.

In the study conducted by Nagitta et al. 2022, AI was employed for evaluating tenders, facilitating the assessment of suppliers' technical and financial proposals. Furthermore, is used in the contract management phase, where it supports in monitoring the performance of suppliers and ensuring compliance with contract terms and conditions.

Xinke et al., 2023 and Delina & Macik, 2023 support the use of AI in various parts of the purchasing process, including supplier selection, warehousing, and logistics. AI technology can improve information exchange in each link of the supply chain, enabling real-time price adjustment with suppliers. In Delina & Macik, 2023 AI supports the prediction of procurement performance, the analysis of transactional data, and the enhancement of data structure for decision-making tasks.

Several papers focusing on public purchasing and government procurement like Gallego et al., 2020 support the identification of potential corruption in the purchasing process. They aid in identifying irregularities and anomalies in the procurement process, such as uncovering unusual patterns in the number of contracts awarded to a specific supplier, identifying abnormal pricing, or highlighting suspicious timing of contract awards.

Fazekas et al., 2022 and Rodríguez et al., 2022 included ML-based functions which support the supplier selection process, contract management, and order fulfillment. Furthermore, they assist in identifying potential risks and opportunities to improve the purchasing process.

Burger et al., 2023 mentioned that various AI methods are used for specific subprocesses with defined inputs and outputs. Between input and output, the strengths of AI come into play and make the process faster and more efficient. The AI processes large quantities of internal data (e.g., supplier and purchase order data) and public data. That includes demand planning, where AI can improve planning when and what to purchase, and supplier selection where AI can assist in selecting suitable suppliers and concluding contracts. Furthermore, in order management AI can ensure the delivery of orders in the quality, quantity, and time contracted. This involves several engineering and transportation interfaces depending on the complexity of the item purchased and the contractual terms. For procurement analytics like Data-driven approaches, likely powered by AI, which can help optimize goals set for expenditures and budgets, supplier and risk assessments, or costing.

AI helps Dixit et al., 2020 identify potential suppliers for procurement and assist in evaluating the performance of suppliers and is used to negotiate contracts with suppliers.

In Mohd & Nohuddin, 2021 AI-based functions support several parts of the purchasing process, including identifying vendors who have previously participated in tenders and their success rate, detecting patterns and trends of suspicious bidding, such as fraudulent alliances and cartels, and assisting in decision-making by providing insights into patterns and trends in the procurement process.

Dor & Coglianese, 2021 they aid in the identification of potential suppliers, evaluation of their capabilities, negotiation of contracts, and monitoring of contract performance. AI also helps in the detection of fraud, waste, and abuse in procurement activities.

In the procurement process, AI lends support to Harikrishnakumar et al., 2019 in strategic purchasing by conducting bid evaluations and facilitating the selection of suppliers. It can also be helpful in predicting the future price of goods and services, which can help in budgeting and planning and also be used to monitor contract performance and compliance.

AI is also used in Jafari et al., 2020 mainly for forecasting, in this case how prices will develop in the purchasing process. This can be used as a guide for selecting suppliers and determining the optimal order percentage from each.

The primary focus for using AI, according to Kusonkhum et al., 2023, lies in identifying potential suppliers, assessing and choosing suppliers, engaging in negotiations, and effectively managing supplier relationships.

In Rodriguez et al., 2021 and Rabuzin & Modrusan, 2019 the tendering sub-process in the purchasing process is supported by machine learning, in (Rodriguez et al., 2021) the prediction of the number of bidders and the estimation of the final price of a tender. It also assists in the prediction of the probability of a tender being awarded in Rabuzin & Modrusan, 2019 the detection of corruption is the main focus.

Ruomeng et al., 2021 is to optimize procurement decisions under price uncertainty. This research focuses on investigating how the use of artificial intelligence (AI) by buyers influences suppliers' pricing strategies in the context of procurement. Specifically, the study examines the impact of two AI capabilities: automation, where buyers use a chatbot to inquire about prices automatically, and smartness, where buyers signal the use of a sophisticated AI algorithm for supplier selection.

The paper authored by Bai & Qiu, 2023 constitutes a research study on the utilization of machine learning, particularly artificial neural networks, for detecting procurement fraud. The primary objective of this study is to construct a machine-learning model capable of predicting the likelihood of fraud in a procurement process by analyzing a predefined set of input data.

The ML-based functions in Jordon et al., 2019 support various parts of the purchasing process, including procurement, delivery, storage, and dispatching. The ML system is used to develop a decision-aided tool that helps in solving complex problems related to these processes.

The commonalities found in the application of AI in the procurement process across the papers:

1. Supplier Selection and Evaluation: AI plays a significant role in identifying prospective suppliers, assessing their capabilities, and selecting the most suitable candidates based on diverse criteria, including cost, quality, reliability, past performance, and more.

2. Demand Forecasting: AI is harnessed to forecast future demand for products or services, providing valuable assistance in inventory management, procurement planning, and optimizing order quantities.

3. Decision-Making: AI assists in making informed procurement decisions, particularly under uncertain conditions. This includes scenarios such as price volatility and commodity procurement.

4. Contract Management: AI aids in the analysis of contract terms, monitoring supplier compliance and performance, and detecting any potential risks or opportunities.

5. Price Prediction: AI-based models are used to predict the future price of goods and services, assisting in budgeting and planning.

6. Fraud Detection: AI plays a crucial role in detecting patterns and trends that might indicate fraudulent activities, thus ensuring the transparency and impartiality of the procurement process.

7. Negotiation: Some papers mentioned the use of AI in simulating negotiation scenarios, thus helping improving purchasers ability to prepare and subsequently achieve more favorable terms.

8. Data Analysis: AI is capable of analyzing vast amounts of data to identify patterns or trends that might not be apparent to humans, providing valuable insights into various aspects of the procurement process.

*3.1.1. Clustering RQ1: Part of the purchasing process*

Clusters of the addressed parts of the purchasing process were created by examining the papers. In the list, the clusters are ranked according to frequency, including all those, which were addressed at least twice. It is noticeable that almost exclusively process steps of strategic purchasing are supported by AI.

| |
|---|
| Supplier Selection |
| Contract Management |
| Supplier Evaluation |
| Negotiation |
| Data Analysis |
| Demand Forecasting |
| Prediction |
| Decision-making |
| Fraud Detection |
| Tender Evaluation |
| Spend Analysis |
| Risk Management |

**Table 4.** Ranking most mentioned purchasing process parts

Strategic purchasing involves long-term planning and decision-making that aim to align procurement activities with overall business objectives and create a competitive advantage. It focuses on building strong supplier relationships, conducting market research, and identifying cost-saving opportunities. Strategic purchasers negotiate contracts and terms with key suppliers to secure favorable deals, ensuring a stable supply of high-quality goods and services. The goal of strategic purchasing is to optimize the supply chain, enhance efficiency, and drive sustainable growth of the organization (Bächle & Lehmann 2010).

Operational purchasing deals with the day-to-day activities involved in procuring goods and services to meet immediate needs and demands. It includes routine tasks such as order processing, invoice handling, inventory management, and coordination with suppliers for timely deliveries. Operational purchasers work with predefined contracts and follow established procedures to ensure the smooth flow of goods and services within the organization. Their focus is on executing the purchasing process efficiently, maintaining appropriate inventory levels, and adhering to budget constraints (Bächle & Lehmann 2010).

*3.2. RQ2: Which goals are pursued through the use of AI?*

The goal of using AI in Impedovo et al., 2023 is to automate the task of supplier document management. This is done to mitigate the risk of suppliers issuing false information about themselves. By automating this process, it can help ensure a more rigorous supplier evaluation, which is crucial in a regulated procurement environment.

The main goal in Chuang et al., 2021 pursued through the use of AI in the purchasing process is to improve the accuracy of demand forecasts.

The goal of using AI in Ruomeng et al., 2021 is to optimize procurement decisions under price uncertainty.

The use of AI in the procurement process aims to increase efficiency, reduce costs, and improve the quality of the procurement process. Furthermore, it endeavors to guarantee fairness and transparency in tender evaluations and contract management, as highlighted in the study by Nagitta et al., 2022.

In Xinke et al., 2023 the goals pursued through the use of AI in the e-commerce supply chain include cost reduction, efficiency increase, and sustainable business development. AI technology can empower each link of the e-commerce supply chain to achieve these goals. For instance, AI can help obtain consumers' purchase intentions on the shopping platform, which is crucial for marketing new products. AI also facilitates a "self-healing" supply chain dataset, enabling real-time visibility into supply chain performance, risks, and opportunities for better-informed end-to-end decisions.

The use of AI in the purchasing process aims to improve procurement performance, enhance the predictive power of data models, and provide insights into the opportunities of different data structures based on data aggregation and transformation. The primary objective is to enhance the efficiency and effectiveness of procurement decisions, as emphasized in the research by Delina & Macik, 2023.

Optimizing procurement decisions under price uncertainty is the goal of Mandl & Minner, 2020. The AI-based DDA is designed to learn optimal purchase policies directly from data, focusing on optimal decisions rather than optimal predictions. The approach aims to minimize costs and improve out-of-sample generalization, which is crucial for making effective procurement decisions in a dynamic and uncertain environment

The main goal in Gallego et al., 2020 and Rabuzin & Modrusan, 2019 pursued through the use of AI is to reduce corruption in the procurement process. Through the identification of potential corruption cases, AI contributes to ensuring a fair and transparent procurement process while promoting the efficient and effective utilization of public funds.

The goals of (Mohd & Nohuddin, 2021) are used to detect and predict fraudulent activities in the procurement process and spot risks of patterns in public expenditures.

The application of AI aims to enhance predictions and pricing through automated AI/ML-based methods, providing more accurate and optimized outcomes. This minimizes error-prone manual activities and allows people to be supplied with less expensive fresh foods more reliably (Jafari et al., 2020).

The goal pursued through the use of AI in Wallimann & Sticher, 2023 is to detect potential collusion in railway infrastructure procurement. The effectiveness of construction and maintenance procurement processes, in efficiently utilizing taxpayers' money, relies on ensuring that bidders do not engage in collusion.

The objectives outlined by Kiefer & Ulmer in 2019 involve attaining more accurate demand forecasts by considering a diverse range of influencing factors. This helps in better managing the supply and demand of products. AI helps in increasing customer satisfaction and reducing tied-up capital by ensuring that only the necessary components are ordered.

Impedovo et al. (2021) aim to assist human experts in efficiently analyzing vast amounts of available data and making strategic decisions concerning the management of supplier relationships, product specifications, and required quantities. The implementation of smart procurement would consequently enable the company to gain a competitive advantage.

Nearly half of the papers have the goal of improving the efficiency of the purchasing process, reducing costs, and enhancing the quality of supplier selection. Furthermore, AI is employed to identify potential risks and opportunities, to improve the purchasing process (Fazekas et al., 2022; Burger et al., 2023; Dixit et al., 2020; Sai et al., 2022; Kieseberg et al., 2022; Dor & Coglianese, 2021;

Harikrishnakumar et al., 2019; Kusonkhum et al., 2023; Ai et al., 2022; Rodriguez et al., 2021; Bai & Qiu, 2023; Jordon et al., 2019; Rodríguez etal., 2022; Lee 2023).

Several commonalities can be identified across the papers regarding the goals pursued through the use of AI in procurement processes:

- Efficiency improvement: AI is consistently applied to automate repetitive tasks, streamline processes, and minimize manual effort, resulting in heightened efficiency within procurement operations.

- Cost reduction: AI is employed to optimize various aspects of the procurement process, such as demand forecasting, supplier selection, and decision-making, to achieve cost savings.

- Enhanced decision-making: By leveraging AI-driven insights and data analysis, organizations can make more informed and data-driven decisions, leading to enhanced procurement outcomes.

- Risk management: AI is harnessed to identify potential risks, such as supplier reliability or contract terms, facilitating proactive risk mitigation and improved risk management strategies.

- Increased transparency and fairness: AI applications contribute to ensuring fairness and transparency in the evaluation of tenders, supplier selection, and contract management.

- Fraud detection and prevention: AI is used to detect potential cases of corruption, collusion, or fraudulent activities in the procurement process, promoting ethical practices.

- Supplier performance improvement: AI facilitates a comprehensive view of supplier performance, enabling effective supplier relationship management and performance improvement.

- Demand forecasting optimization: AI-driven demand forecasting aims to improve inventory management, reduce stockouts, and enhance customer satisfaction.

- Data-driven procurement decisions: AI helps in making optimal procurement decisions based on data analysis and learning directly from historical data.

- Real-time visibility and data-driven insights: AI provides real-time visibility into supply chain performance, risks, and opportunities, enabling data-driven decisions.

- Integration of emerging technologies: Several papers mention the integration of AI with other emerging technologies like IoT, big data management, and chatbots to enhance procurement processes further.

- Procurement fraud detection and corruption prevention: AI is used to identify suspicious patterns, predict potential corruption, and reduce the risk of unethical procurement practices.

Overall, the commonalities revolve around optimizing procurement operations, improving decision-making, promoting fairness and transparency, and reducing costs and risks, ultimately leading to efficient and effective procurement processes.

*3.2.1 Clustering RQ2: Pursued goals*

In Table 5, the pursued goals are ranked according to the number of mentions. Traditionally, the main goal is cost reduction and secondly, increasing efficiency, which cannot always be clearly differentiated from cost reduction.

| **Pursued goals** |
|---|
| cost reduction |
| improve efficiency |
| decision support |
| predict corruption |
| accurate forecasting |

**Table 5.** Ranking most mentioned goals

*3.3. RQ3: Which technology or method is used?*

The goal of using AI in Impedovo et al., 2023 is to automate the task of supplier document management with Robotic Process Automation (RPA).

Chuang et al., 2021 highlight the utilization of predictive analytics, a form of AI, for demand forecasting. It also mentions the use of data pooling, which is built upon temporal aggregation, a popular method in business forecasting. The document also mentions the use of feature engineering, which is a process of creating new input features for machine learning, and the use of regression models, such as Lasso and elastic net, that can handle high-dimensional inputs.

In Mandl & Minner's 2020 study, the technology used is a nonparametric, data-driven approach that utilizes real-time feature data, including economic indicators, to address the problem at hand. The method involves the use of mixed integer linear programming (MILP) under cost-minimization objectives. The approach also combines optimization with regulation gained through the use of machine learning to extract decision-relevant data from noise.

The document Xinke et al., 2023 mentions the use of AI technology, specifically the Automated Guided Vehicle (AGV), intelligent transportation system, for warehousing in the e-commerce supply chain. The AGV system plans distribution routes through a method known as the computer artificial potential field method. AI and advanced analytics are also employed to replace certain low-skilled and repetitive tasks, like material handling and inventory control, as well as certain skilled labor roles that involve statistical and predictive modeling and analysis.

The paper by Delina & Macik, 2023 discusses the use of machine learning models and algorithms for prediction tasks. In particular, the research employed a stacked ensemble model for in-depth analysis. The model underwent training with a five-fold cross-validation method. The paper's methodology focused on comprehending the fundamental data structure provided by the EKS platform and enhancing it to suit various decision-making tasks. The technology employed by Mandl & Minner, 2020 is a nonparametric, data-driven approach that utilizes real-time feature data, such as economic indicators, to solve the problem effectively. The method involves the use of mixed integer linear programming (MILP) under cost-minimization objectives.

In their study, Fazekas et al., 2022 discuss the implementation of advanced ensemble-based methods, such as Random Forest and Gradient Boosting Machine (GBM), which harnesses the collective predictive strength of numerous decision trees. These models utilize the same set of predictors as logistic regression. Among these models, the GBM algorithm demonstrated superior performance on external validity tests, offering an opportunity to explore the significance of various indicators in enhancing prediction accuracy.

The following technologies and methods are used in AI-based functions (Mohd & Nohuddin, 2021):

- Association Rules: This is a method used to extract meaningful correlations, frequent patterns, and associations between data sets in a repository. It is used to explore the set of rules from a large dataset by extracting all the relationships between data.

- Apriori Algorithm: This technique is applied for frequent itemset mining and association rules in the context of mining evidence related to fraudulent simulations of competition in procurement.

- Feature Selection Classifier: This is used to eliminate irrelevant and/or overlapping features and retain only relevant features. It helps in improving the algorithm's accuracy, greatly reducing the number of features in the dataset, thus improving efficiency, and increasing performance.

- Self-Organizing Maps (SOM): This machine learning technique is utilized for visualizing and validating property relationships between the generated rules. It provides a clear way of summarizing complex multidimensional data and can be easily understood and interpreted.

In their article Sai et al., 2022 discuss the implementation of AI-powered chatbots integrated with existing Enterprise Resource Planning (ERP) systems to automate the procurement process. The chatbot developed in the study encompasses various features, including supplier preference order through Analytic Hierarchy Process (AHP), responses to frequently asked queries, and essential procurement metrics.

Furthermore, Robotic Process Automation (RPA), a form of business process automation technology driven by AI and a digital workforce, finds application in the supply chain to decrease time, effort, and potential errors associated with audit maintenance.

In Kieseberg et al., 2022 machine learning is used to learn from data, identify patterns, and make decisions with minimal human intervention. In detail, these are the following technologies:

- Natural language processing (NLP): This technology is used to analyze text, such as contract terms or supplier reviews. It is often used in contract analysis and supplier evaluation.

- Simulation: AI can simulate various scenarios, such as negotiation strategies or demand fluctuations, to support decision-making.

- Data analysis: AI can analyze large amounts of data to identify patterns or trends that may not be apparent to humans. This is used in many aspects of the purchasing process, from demand prediction to risk management.

The paper Kusonkhum et al., 2023 mentions the use of machine learning in the procurement process. In particular, the article highlights the utilization of the KNN (K-nearest neighbors) classification algorithm to create a model for awareness and information sharing, aimed at enhancing the quality of the existing construction information management system. Additionally, artificial neural networks (ANNs) and other models are mentioned for computing the cost and timeline of construction projects. The article also emphasizes the importance of optimizing hyperparameters, a critical aspect of training machine learning models.

The paper Rodriguez et al., 2021 mentions the use of machine learning algorithms, including traditional regression methods like linear regression and random forest, as well as less investigated paradigms like isotonic regression and artificial neural network models. Additionally, the learning process is based on minimizing a cost function (also known as a loss function) that evaluates the performance of the network for the given task. Indeed, backpropagation is commonly utilized to iteratively adjust the weights associated with the connections in neural networks. It helps optimize the model's performance by minimizing the error between predicted and actual outputs during the learning process.

For the prediction of public procurement corruption in Rabuzin & Modrusan, 2019 the following technologies are used:

- Text Mining and Natural Language Processing (NLP): Text mining techniques are utilized to examine the contents of the tender documentation. The application of NLP methods allows for the extraction and optimization of text from the tender documentation, enabling a more profound comprehension and effective utilization of the textual information.

- Machine Learning: Machine learning methods are used to improve the system's performance through experience. The prevailing text classification methods encompass support vector machines, naive

Bayes, decision trees, logistic regression, K-nearest neighbors (KNN) classification algorithms, genetic algorithms, and diverse neural networks. These techniques play a crucial role in categorizing and classifying textual data for various applications.

- Data Preparation and Tokenization: A special program in Python is used to download tender documents and prepare the data for further processing. The content is tokenized, i.e., translated into separate words or vectors.

- Data Normalization and Conversion: Normalized token words are converted into numerical, computer-comprehensible form. The frequency of each word's occurrences within a specific document and across all documents is calculated. This information enhances in understanding the significance and relevance of words within the given corpus of text.

- Modeling and Evaluation: Different machine learning models are trained and tested on the data. The models used include Naïve Bayes, Logistic regression, and Support Vector Machines algorithm. The results are observed through metric measurements such as accuracy, precision, and recall.

The technology or method used Kiefer & Ulmer, 2019 include:

- Artificial Neural Networks (ANNs): ANNs have been widely employed for forecasting purposes in research. AI forecasting methods have been steadily integrated into the business practices of large companies, enabling more accurate predictions and informed decision-making. The adoption of these advanced techniques is enabling organizations to enhance their planning and strategic operations.

- Machine Learning (ML) and Deep Learning (DL): These are subsets of AI that learn through training with huge data sets. ANNs are utilized in predictive maintenance algorithms to analyze data collected from Internet of Things (IoT) sensors. By processing this data, ANNs can reliably predict potential defects or failures in machinery or equipment, enabling proactive maintenance measures to prevent unexpected downtime and improve overall operational efficiency.

- Autoregressive Integrated Moving Average (ARIMA): Forecasting employs various methods, including both judgmental and statistical approaches. While companies predominantly rely on judgmental and statistical techniques for forecasting, AI-based methods like Autoregressive Integrated Moving Average (ARIMA) have also been widely used in research to enhance prediction accuracy and efficiency. These AI-driven approaches provide valuable insights and predictive capabilities, empowering organizations to make well-informed and data-driven decisions to meet their forecasting requirements more effectively.

- AI Packages: Packages like TensorFlow are used to distribute AI methods more widely, reducing the complexity of using them.

- Big Data: The amount of data is increasing rapidly, and the price of storing enormous amounts of data is decreasing. The data serves as the training dataset for AI models.

Various technologies and methods are used in AI-based procurement (Impedovo et al., 2021). These methods fall under the umbrella of operational research and are widely employed for decision-making and optimization tasks in various fields. They include:

- Multicriteria and Multi-attribute Decision Making methods (MCDM and MADM): They are used to evaluate and compare multiple alternatives based on multiple criteria or attributes.

- Multi-objective Programming (MOP): It is to optimize multiple conflicting objectives simultaneously, taking trade-offs between them into account.

- Mixed Integer Programming (MIP): Used to optimize problems that involve both continuous and discrete decision variables.

- Dynamic Programming: Used to solve problems with overlapping subproblems by breaking them down into smaller subproblems and finding an optimal solution for each subproblem.

These methods are valuable tools for tackling complex decision-making and optimization challenges, enabling businesses and researchers to find better solutions and make informed choices. Machine learning methods are used as well, including supervised methods like neural networks, support vector regression (SVR), support vector machines (SVM), logistic regression, rule learning, k-nearest neighbors, linear regression, and native bayes. Moreover, methods like process mining, fuzzy association rule mining, and Markov decision process are utilized.

*3.3.1 Clustering RQ3: Used technology, technique or method*

Table 6 shows the clusters formed for the most frequently mentioned technologies, techniques and methods.

| **Technology** |
|---|
| Chatbots |
| Data Analytics |
| Data mining |
| Data-Driven Optimization |
| Deep Learning |
| Feature Selection |
| Machine Learning |
| Natural language processing |
| Neural Networks |
| Robotic Process Automation |
| Simulation |
| Text Mining |

**Table 6.** Most mentioned groups of technology

## 4. DISCUSSION

The assistance of e-procurement processes through AI holds significant importance for several reasons. Firstly, it aids in the evaluation of vast amounts of data, and secondly, it streamlines numerous individual processes inherent in the procurement workflow. AI can and is already used to identify patterns in the area of supplier evaluation and to identify corruption, especially in the public sector. Other important points are also the forecasting of price development and the prediction of future order quantities.

There are many aspects where AI can help streamline the procurement process. Several of the examined articles had the goal of increasing efficiency and reducing costs. By looking at the process from start to finish, AI helps uncover hidden costs. Analysis of supplier behavior and simulation of negotiations are some further examples of the possible use of AI in the main process. The AI algorithms used have hardly been disclosed so far, possibly for reasons of confidentiality. While various algorithms are available for use, a specific use case showcasing the relevant algorithms' application in spotting trends would be highly beneficial. Over the years, expertise in this field has predominantly focused on supplier selection, making it one of the most extensively studied issues in the procurement domain.

As evaluated in Chapter 3.1.1, the use of AI in procurement is still primarily in the field of strategic purchasing. One assumption is that operational purchasing in companies is already very well

supported by technologies that have existed for some time, such as desktop purchasing, round trip, EDI, and purchasing portals, and that the advantages of AI are therefore not yet seen as too small.

*4.1. Restrictions*

As with any SLR, there are also limitations to this study.

The biggest influencing factor is the choice of search terms. Author have tried to make this SLR optimal. The result of the literature research depends on the choice of search terms as well as on the structure of the search query and the access to the different databases. Although the search was carried out very conscientiously, it cannot be ruled out that further papers on the subject exist but were not found.

## 5. CONCLUSIONS

The use of AI technologies in procurement is increasing, although some aspects are still understudied.

The results of this SLR show that parts of the strategic part of the purchasing process can already be supported by AI, while the operative part has received little attention in the literature. This conspicuousness in the AI support in operational purchasing by AI could be worth further consideration.

The current trend that software-manufacturers are increasingly integrating AI into applications will certainly receive an increased level of support and will transform all areas of the application system.

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