EPICS: Pursuing the Quest for Smart Procurement with Artificial Intelligence

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Abstract. E-procurement involves the set of activities, performed in the manufacturing business, to requisite, order, and purchase goods and services online, usually on a periodic and large-scale basis from a supply chain. Every activity is a decision-making process that rapidly becomes infeasible by human procurement experts, often due to a large amount of information to be taken into account, coming from different sources. To overcome this limitation, smart procurement based on artificial intelligence has been proposed. However, the majority of the literature only focuses on specific procurement-related problems, only from a supply chain perspective, without providing a holistic and encompassing solution. In this paper, we identify the 4 pillars of smart procurement based on artificial intelligence and discuss how to accommodate implementations into the preliminary architecture of the EPICS platform.

1 Introduction

E-procurement is the digitization process of the procurement of goods and services undertaken by a company, from the call for tenders publication to the payment, through the use of information technology facilities like the Internet, online bidding, and auctions, and so on. The benefits of e-procurement are manifold, including i) improved interaction efficiency between procurement actors, ii) enhanced productivity, by spending the time saved, thanks to process automation, on strategically meaningful functions and tasks, and iii) increased awareness of spending resulting in the reduction of costs.

In parallel with the rising importance and adoption of e-procurement, the set of data collected by companies that use it has grown increasingly large and very complex, making it difficult and time-consuming to analyze and extract useful information from it. To deal with this problem, recently much focus has

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been placed on smart procurement, that is the set of technologies used to support human experts in analyzing the huge amount of available data and taking strategic decisions related to, for example, the management of supplier relationships, or the definition of product specifications and quantities needed. Due to its characteristics, a good application of smart procurement would lead to the achievement of competitive advantage for the company.

Artificial intelligence has been proposed as a key technology behind smart procurement since it can be used to formulate hypotheses on data, generate suggestions on a particular decision, and identify patterns in a large amount of data. However, the vast majority of the literature only discusses artificial intelligence applications to very specific procurement problems that, in their turn, remain somewhat disconnected from each other, thus failing in delivering a complete and sound view on the procurement to the users. In this paper, we identify the 4 pillars of smart procurement and discuss how to accommodate intertwined implementations into the preliminary architecture of the EPICS platform, developed in the scope of the EPICS research project conducted with both industrial and academic partners.

2 Related Work

Many works have been proposed to analyze the problems and challenges characterizing smart procurement, proposing new approaches and techniques to face them. In particular, a considerable body of research is concerned about two perspectives: i) monitoring the performances of, potentially unknown, suppliers and selecting the optimal ones, and ii) monitoring and forecasting adverse procurement events involving materials (goods or services) and suppliers. Methodologically, the proposed solutions exploit either *operational research* – such as multicriteria and multi-attribute decision making methods (MCDM and MADM), multi-objective programming (MOP), mixed integer programming (MIP) and dynamic programming [15,18,12,17,5,10]– or *machine learning* methods.

The tasks of *supplier selection* and *performance evaluation* have been tackled with both supervised and unsupervised methods. Among the supervised ones, neural networks [7], support vector regression (SVR), support vector machines (SVM) [13,19], logistic regression [6], rule learning, k-nearest neighbors, linear regression, naïve bayes have been used [3,1,16,4]. However, in the context of smart procurement, they seem to be at an early stage, due to the lack of publicly available datasets of labeled suppliers, a requirement not always easy to satisfy due to the subjective nature of the evaluation. As concerns unsupervised model, process mining, fuzzy association rule mining, and Markov decision process have been used to solve the aforementioned problems [9]. Clustering methods and neural networks have been also proposed for discovering homogeneous groups of suppliers (*segmentation*) [1,2]. Furthermore, unsupervised approaches have been also used for supplier classification [1].

The tasks of adverse procurement *event detection* (e.g. fraud or failure detection) cast anomaly detection problems, whereas the tasks of adverse procurement

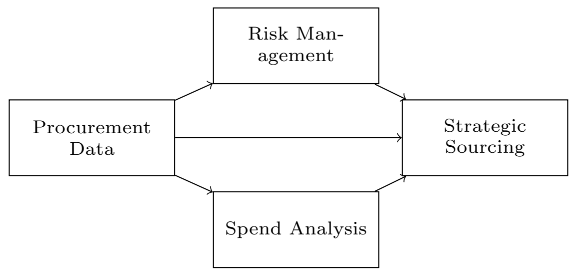

Fig. 1: The smart procurement pillars in the EPICS platform.

event forecasting (e.g. failure or demand forecasting) cast forecasting problems. Specifically, in the case of event detection, process mining techniques have been exploited to detect anomalous events occurring during procurement process executions [14]. Alternatively, some works tried to solve the problem using a supervised setting through bayesian networks, naïve bayes and decision tree learning algorithms [11]. In the case of event forecasting, instead, unsupervised learning methods, e.g. association rule mining and clustering, have been used for solving failure and demand forecasting problems [8].

3 Case study: the EPICS platform

In this section, we present the EPICS (*E-Procurement Innovation For Challenging Scenarios*) platform: a proprietary e-procurement solution, designed and developed by NIUMA as a research collaboration with public Italian universities, that aims at empowering the performances of procurement offices in buyer companies with the help of artificial intelligence.

The EPICS platform is a multi-tenant, multi-cloud, and microservices oriented architecture implementing a full-fledged solution guiding the procurement offices in initiating, managing, and monitoring the execution of procurement-related processes, such as requesting offers and quotations, inviting suppliers to auctions, managing their bids, thus ensuring the visibility and the governance of the whole procurement.

To accommodate smart procurement capabilities into the EPICS platform, firstly, we have extensively studied the relevant literature on the four pillars of smart procurement (namely, procurement data, risk management, spend analysis and strategic sourcing - as depicted in Figure 1) and spotted interesting problems. Then, we have deployed solutions to these problems into microservices, mostly serving machine learning models to the production environment.

3.1 Procurement Data

Procurement data, lying at the EPICS platform core, consists of quantitative and qualitative attributes of entities, mostly materials (goods or services) and suppliers, as perceived from the buyer company and involved in the procurement processes. Although seemingly similar, procurement data may profoundly differ from supply chain data. The difference lies in their scope of observation: while supply chain data depicts an often incomplete view of how companies are entangled around the globe in buyer-supplier relationships, procurement data depicts the complete scenario of the supplying relationships engaged by the buyer company concerning the immediate, well known, qualified suppliers that are continuously monitored over time.

It is evident that procurement and supply chain data only partially overlaps: procurement data neglects information related to suppliers of the immediate suppliers, while supply chain data does not account for details of transactions between a buyer company and his suppliers, which are often secretly kept. As a consequence, for smart procurement to be effective, there is a need to collect and store procurement data coming from different, both internal/external and structured/unstructured, data sources such as the procurement platform itself, the ERP systems, and the information providers available online.

Available data necessitates continuous aggregation and cleaning to stay up-to-date. This is particularly relevant, for instance, when qualifying both materials and suppliers by matching their publicly known characteristics against what is self-declared on written documents and certifications that have been requested by the buyer during the qualification process. Such processing activity is usually human-made and, therefore, time-consuming and error-prone. To mitigate this problem, artificial intelligence and machine learning techniques may represent an added value for EPICS because they should help, in principle, to i) automatize the tasks of data collection, integration, and evaluation (with process mining and *robotic process automation* techniques) and ii) increase the overall accuracy of the results (with machine learning techniques).

Currently, EPICS integrate different machine learning models and techniques as follows: given a set of documents envelopes – each of them containing documents such as DURC, ISO, etc. – they are firstly acquired by using OCR systems (*intelligent document recognition*) and converted into a set of electronic documents that are firstly classified into a taxonomy of known document types, and pruned away in case of anomalous ones; and, secondly, they are further processed via natural language process techniques. In particular, *named entity recognition* methods are employed to recognize the different parts of an envelope to convert it into a structured record containing the relevant fields extracted from the original document.

3.2 Risk Management

Managing risks in the e-procurement means solving three problems: i) *identifying* the exposure of suppliers and materials to one or more risk categories, ii) *analyzing* the association between risky suppliers/materials and the negative events recorded while executing business processes within the buyer organization, and iii) *evaluating* the likelihood and the impact of risky elements on the overall business.

Risk-related data is often implicitly contained in procurement data and needs to be exposed in a risk warehouse. Here, risky elements (materials and suppliers) are qualified by assigning them one or more risk categories to which they are exposed. Such an activity, referred to as *risk identification*, qualifies materials and suppliers based on their quantitative features, eventually computing indirect risk KPIs. However, identifying risky elements is not always straightforwardly done because i) KPIs interpretation is often subjective, and ii) the risk predicate is not known in advance or it is hard to be made explicit. Therefore, in EPICS, machine learning models significantly contribute to inferring the risk predicates from data in the risk warehouse. Then, risky elements are associated with event logs generated during business processes executions seeking correlations or frequent patterns denoting the root causes of the negative events.

3.3 Spend Analysis

Managing the spend means keeping track overtime of how the budget is deployed to the purchase of different materials, and, therefore, to the different suppliers in charge of supplying them. Controlling the spend over time allows to the buyer to spot saving opportunities and efficiency pitfalls. For an accurate spend analysis, three conditions should be met: i) spend data needs to be continuously cleaned to increase the spend visibility, ii) cleaned data should be stored in one or more data warehouses and referred to as *spend cubes*, and iii) stored data should be processed with advanced techniques in order to find relevant trends and patterns.

In particular, the spend cleaning aims at standardizing and aggregating every relevant attribute, concerning materials and suppliers involved in the spend records, that could potentially fragment the observed spend if left untreated. For example, the cleaning could collapse two product codes denoting the same material into a single one, thus letting the user noticing that it is currently purchasing the same good (or service) with different prices by requesting two distinct product codes to different suppliers. Such an activity of *material/supplier segmentation* can be immediately solved by clustering algorithms or by *entity linking* (also known as *deduplication*) methods aiming at discovering the names referring to the same entities (materials or suppliers). Furthermore, machine learning models are potentially useful also during the spend analysis step, where *relational learning* algorithms designed for multidimensional data cubes manage to discover more complex and expressive spend patterns and trends.

3.4 Strategic Sourcing

Strategic sourcing refers to the process of developing an optimal procurement plan by establishing durable supply relationships with reliable suppliers. Such a plan is built by i) *selecting the right materials* according to the buyer's needs, ii) *continuously evaluating* the, potentially unknown, suppliers for the selected materials, and iii) *selecting the suppliers* by maximizing different, often contrasting, criteria considering all the possible alternatives and outcomes. Due to the nature of this task, the strategic sourcing cannot be performed independently of the other pillars of smart procurement: it needs to elaborate and gain insights from procurement data, consider the risks highlighted by the risk analysis (e.g., the sole-sourcing risk, whereby a material is supplied by only one supplier), and, lastly, it should be guided by the valuable information extracted during the spend analysis.

Strategic sourcing is one of the most important components of the supply chain because, thanks to it, companies can establish and maintain long-term relationships with the suppliers, resulting in timely deliveries with consistent quality, lower inventory costs, and the possibility of product improvement. To achieve this goal, the tasks of supplier recommendation and selection acquire remarkable value. Both tasks can be carried out taking into account different criteria, either subjective or objective, elaborated on the basis of the available procurement data or, more generally, supply chain management data. Often, the analyzed criteria used to evaluate suppliers include, but are not limited to, their economic power, financial data, or the quality of the services or the products supplied. Machine learning could play a key role in the recommendation of new suppliers through the use of *recommender systems*, software able to provide suggestions on the basis of the user preferences. At the time of writing, the EPICS platform leverages a recommender system that provides suggestions on the basis of the interactions between buyers and suppliers. Such suggestions are shown to the users as a ranking sorted by a score of relevance, that is, the recommendation score.

4 Conclusions and Future Work

In this work we have discussed how artificial intelligence supports the four main pillars in the smart procurement process, namely: procurement data, risk management, spend analysis, and strategic sourcing. In particular, based on evidence from the scientific literature, we discussed a framework, drawn from the blueprint of the EPICS platform, in which to accommodate actual machine learning solutions to the aforementioned procurement problems. Different from the existing approaches, in which procurement problems are separately solved, our attempt paves the way towards the actual adoption of intelligent solutions encompassing the whole spectrum of the procurement processes.

Since every problem can be solved by computational approaches drawn from a wide range of algorithms, there is room for a large number of empirical validations. For this reason, as future research directions, we aim at independently gaining insight into the performances of every proposed solution, perhaps by quantitatively evaluating the performances (e.g.: accuracy, efficiency, etc.) in a comparative setting against existing solutions.

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