KI 2021 DC: AI Methods in Procurement

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Abstract. Artificial intelligence is a research area that attempts to design mechanisms allowing machines to develop intelligent behavior. It is a key technology for procurement and its usage is still in its infancy. For instance, the Volkswagen "Procurement Strategy 2025" stresses the potential of artificial intelligence to optimize processes and structures - and this applies to the automotive industry and other procurement organizations worldwide. Yet, only a few have successfully integrated artificial intelligence methods into their operations and across their supply chains but is recently starting to emerge. This constitutes a research opportunity on how artificial intelligence increases its performance. The Ph.D. is set up as external doctoral research supported by Porsche and the Volkswagen AutoUni in cooperation with the University of Mannheim. The research goal is to examine and exploit ideas on how methods of artificial intelligence can be utilized in the procurement function. Procurement is often one of the last functions to be digitized. However, it must keep up in the race against the capabilities of our negotiation partners in the sales organizations of our suppliers worldwide.

Keywords: Procurement, supply chain management, applied AI

1 Introduction and motivation

Today, buyers spend on average 52 percent of their time on transactional activities (Vollmer et al., 2018). Likely there will be fewer people especially in operational procurement that perform essentially routine tasks underlying the "British National Public Radio's Planet Money" where procurement clerks having a 98 percent chance of being automated (Zagorin, 2019). The Chief Information Officer of Porsche, Matthias Ulbrich highlighted the importance of demand forecasting for functions spanning from sales to procurement and production (MIT Sloan, 2020). The first study focused on the total cost of ownership prediction of procured items comparing AI methods with previously used methods. Suppliers often utilize the switch of the power balance after project nomination to increase their prices and margins (Bode and Peters, 2016, Ronellenfitsch, 2017, Spreitzenbarth and Stuckenschmidt, 2020). Therefore, the prediction of the total cost of ownership of procured items was chosen in particular since costs induced due to various change orders over the product life cycle make cost planning difficult. The case study has been conducted at a German automotive manufacturer based on three interlinked data sets. Naïve algorithm models are evaluated as baselines for quality of cost prediction based on nomination data. In addition, data on engineering and production change orders are utilized since they often lead to price increases. Lastly, cost breakdowns have been considered, as they are applicable during several phases of the product lifecycle. The study shows practical ways to break down uncertainty into measurable quantities within the total cost of ownership model (Spreitzenbarth and Stuckenschmidt, 2020). The work confirms previous research that in particular regression trees and Bayesian optimization can reduce the uncertainty inherent in supplier selection (Brochu et al., 2010, Jain et al., 2014). The conceptual framework of the study has been built upon in part of the author's master thesis "Cost Engineering for the Procurement of Embedded Software" conducted in 2014 at the Karlsruhe Institute of Technology with the support of IBM Research. The research idea was presented at the International Purchasing and Supply Education and Research Association (IPSERA) Doctoral Workshop and the European Research Seminar (ERS) in digitally 2020. The study has been accepted to be published at the major cost engineering conference Association for the Advancement of Cost Engineering (ACCE) in June 2021.

2 Research question and related work

The research is driven by the question of how to utilize AI methods in procurement. Therefore, the second project was a conceptual literature review for artificial intelligence in procurement. The literature is classified along the strategic, tactical, and operational dimensions of procurement (van Weele, 2014) and according to the Association of Computing Machinery framework of computing methods (ACM, 2012). In total, 210 works at the intersection between AI considered together with machine learning techniques and procurement application are described, compared, and assigned along these dimensions to eleven derived use caster clusters. Lastly, eighteen expert interviews have been conducted to assess the clusters in terms of their business case and ease of implementation (Spreitzenbarth et al., 2021a). This work was presented at the major procurement conference IPSERA in digitally in March 2021 and discussed among fellow doctoral students at the IPSERA doctoral workshop. The author was glad to be asked to serve as a reviewer for other interesting works in the overarching domain of digital supply chain management for the conference as well as stage manager volunteer at the conference. The paper is currently in review for the special call of the associated Journal of Purchasing and Supply Management. Due to current popular interest, a summary might be published in a supply chain management association magazine such as Best in Procurement of the German BME.

Building upon the review, a comparative study has been set up as a master thesis to analyze the available data and the needed decisions from a procurement and sales perspective. Thereby, sales and procurement can be considered as two sides of a coin that struggle against one another for relative competitive advantage for negotiations. In McKinsey's "The State of AI" survey the business functions in which organizations adopt AI are largely consistent over the years with service operations, product development, marketing and sales (Balakrishnan, 2020). Some expect that the supply function is less likely to benefit from the application of AI methods (Nowosel et al., 2015, Bauer et al., 2017, Hofmann et al., 2017) emphasizing the potential benefits in finance, production, and sales. A survey could be conducted to consider a broad perspective on the aspects for needed decisions, available, and analytical maturity level. This approach may be contemplated with workshop-style discourses, e.g., at major conferences considering the perspective from Europe, North America, and China where most associated research is conducted. This may lead to further suggestions of how procurement can speed up in the analytics race (Spreitzenbarth et al., 2021b). The concept has been accepted for presentation at the ERS conference in June 2021.

3 Approach and evaluation

The research approach is to apply different research methods to highlight and realize the potential of AI in procurement at concrete examples. Currently, further projects are evaluated in cooperation with the advisors. These are in particular a bundling generator that takes as an input to sourcing planning across the organization and outputs prioritized options for bundling through natural language understanding and supervised learning. Today on average 65 percent of the value of a company's products or services is derived from its suppliers (Vollmer et al., 2018). While well researched, even minor improvements to the supplier selection process may save millions to the financial bottom line (Pal et al., 2013). Procurement generates a much data; however, available data is not always enough (Gruenen et al., 2017, Handfield et al., 2019). In procurement, the added value can be increased by bundling demands of different projects, different suppliers, and different organizations within the organization. Typically for instance in the automotive sector, bundling is procedurally and organizationally ensured by material group management (Monczka et al., 2019). Thereby, each specialist group records its upcoming awards in an individual, manual award plan. This data is primarily used for reporting and tracking. An evaluation using different formats requires manual effort. In complex organizations, there is often no automatic data exchange and communication across so many different stakeholders is inherently slow and complex. Therefore, cross-supplier potential is not visible. Supplier potentials only become evident in the final decisions' committees, often too late to be bundled and achieve further potential savings. A system was drafted that takes the sourcing planning from different formats across the organization as input and provides recommendations to bundle tenders continuously learning through feedback over time, e.g., through supervised learning. Not only could further cost reductions be achieved but also the sourcing planning process and its quality improved as better data input leads to better suggestions making the cost reduction potential transparent to management (Spreitzenbarth et al., 2021c). This bundling generator prototype aims to increase communication within the procurement teams in order to generate prioritized proposals for bundling options to identify and exploit further savings. This research has been accepted at the European Operations Management Association (EurOMA) conference in July 2021 as well as the EurOMA Doctoral Workshop. Target publication is the associated European Journal of Operational Research (EJOR).

Being able to predict future behavior is an important capability (Houy et al., 2010, Evermann et al., 2017). Lastly, a simulation has been drafted to solve the sizing problem of an organization through a proposed value function for supporting functions such as procurement. Executives are asking themselves, how many people do I need to fulfill my role? Consultants may provide an answer utilizing benchmarking, e.g., in procurement managed spend by buyer. Yet, this number is subjective as support functions deal with different environments, internal structures, and expectations. Recently, lean and agile principles have been applied to these functions that may be understood as workflow systems delivering value to the organization. Thus, a workflow system is presented that depending on inputs such as total spend, diversity of requisitions, and company strategy - through the internal delivery organization with the people, culture, and processes - is delivering output in terms of cost savings, processing speed, and decision quality (Richardson, 2008, Patrucco et al., 2020). The answer is not only relevant for buyers, but also for controllers, work councils, and maybe even deans wanting their departments to be on top of the pyramid. The concept was accepted for presentation at the International Conference of the System Dynamics Society (SDS) doctoral workshop. Following open science principles, raw data is included in a findable, accessible, interoperable, and reusable way (Brereton et al., 2007, Munafò et al., 2017). Future research can build upon it or reproduce the working prototype available at Figshare under the creative commons license (Spreitzenbarth, 2021).

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