Designing an AI-enabled bundling generator in an automotive case study

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Abstract

Procurement and marketing are the main boundary-spanning functions of an organization. Some studies highlight that procurement is less likely to benefit from artificial intelligence emphasizing its potential in other functions, i.e., in marketing. A case study in the automotive industry of the bundling problem utilizing the design science approach is conducted from the perspective of the buying organization contributing to theory and practice. We rely on information processing theory to create a practical tool that is augmenting the skills of expert buyers through a recommendation engine to make better decisions in a novel way to further save costs. Thereby, we are adding to the literature on spend analysis that has mainly been looking backward using historical data of purchasing orders and invoices to infer saving potentials in the future – our study supplements this approach with forward-looking planning data with inherent challenges of precision and information-richness.

Keywords: Artificial intelligence, purchasing-marketing interface, procurement, B2B marketing, bundling problem.

1. Introduction

Artificial intelligence (AI) is a research area that attempts to design mechanisms allowing machines to develop intelligent behavior (Russell and Norvig, 2020). Information technology and information systems are enablers for successful supply chain management that stems from intelligent and coordinated decision-making throughout the network (Pflaum et al., 2022). The automotive industry is strongly impacted by digital technologies (Dremel et al., 2017). Manufacturers and suppliers need to fundamentally transform their business processes and organizational structures to improve their ability to make evidence-based decisions (Hess et al., 2016).

In this study, the design science approach and information processing theory are applied in a case study in the automotive industry. The developed artifact is built to support the focal organization to make better decisions, and thereby further drive down material and service costs by suggesting to the buyers possible bundles of external demands based on data.

Research question: How to design a module to bundle purchasing requisitions to identify further saving potentials?

This is a relevant and complex optimization problem in the automotive industry as for instance a typical car at Ford has around 40,000 parts from 1,200 direct suppliers (Schuh et al., 2022). Generally, today more than half of the value of a company's products is derived from its suppliers (Vollmer et al., 2018). Design principles may be inducted from the developed artifact (Denyer et al., 2008) that in practice could extend existing technological solutions for procurement teams providing value, especially to larger organizations considering requisitions planning data in addition to traditional historical spend analysis.

2. Related works

While research on artificial intelligence has made strong progress in a relatively short time, leading to a high number of applications in diverse settings, organizations are still in the process of understanding and effectively implementing AI technologies (Hofmann et al., 2019). Its vision stretches outside the domain of human capabilities and is often referred to as a major component of the fourth industrial revolution (Syam and Sharma, 2018). Digitalization changes both buying and marketing processes with major implications for industrial marketing and operations management (Mahlamäki et al., 2021).

In this study, the wording AI is utilized as an umbrella term including machine learning, i.e., unsupervised learning and neural networks for better readability that is understood as a system's capability to correctly learn from data, using those learnings to achieve specific goals and tasks through flexible adaption (Kaplan and Haenlein, 2019). Now, what are the specificities of AI among the other founding

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technologies of the fourth industrial revolution such as robotics, the internet of things, or 3D printing?

2.1 AI in B2B marketing and procurement

AI technologies provide manifold opportunities for business-to-business (B2B) marketers, and they will revolutionize the tasks and processes that marketers execute today (Mero and Keranen, 2019). While marketing is the process by which companies engage customers, build customer relationships, and create customer value to capture value from customers, sales is generally considered to be part of marketing and can be defined as a business system required to effectively develop, manage, enable, and execute a mutually beneficial, interpersonal exchange of goods or services for equitable value (Kotler and Armstrong, 2018). In the business-to-consumer (B2C) context, organizations such as Amazon, Google, or Alibaba might generate more data in a day than a typical procurement or marketing organization of a classical manufacturer in a year. Literature has already highlighted the benefits of AI adoption in B2C contexts (Kushwaha et al., 2021). However, the application in the B2B area is still under-investigated.

Already today, buyers are increasingly faced with suppliers operating on a different digitalization level (Aben et al., 2021; Spreitzenbarth et al., 2021). Procurement is seen as reverse marketing by many scholars (van Weele, 2018). Yet, there are many search hits, what marketers can learn from buyers but interestingly not the other way around (Spreitzenbarth et al., 2021). Procurement also called purchasing or the supply management function can be defined as the acquisition from an external source at the best possible cost to meet the needs in terms of quality, quantity, time, and location and must deal with conflicting targets including time, cost, and quality constraints (van Weele, 2018). Procurement organizations are commonly divided into direct procurement focusing on items that are built into the resulting products such as brakes, tires, or batteries and indirect procurement focusing on internal demands such as engineering or logistics services (Monczka et al., 2020).

When considering the supply chain as an integrated process of plan, source, make, deliver, return, and enable spanning from the supplier's supplier to the customers' customer (van Weele, 2018), procurement as well as sales and marketing are boundary-spanning functions that are connected internally through production or service delivery. The challenges faced on both sides are connected, i.e., through the demand planning process. For procurement, forward-looking requisition planning should be based upon constructive demand planning, whereupon bundles can be created to aggregate demands. Similarly in marketing, when devising bundled products, it can be useful to receive cost and capacity feedback from the supply base consolidated by procurement. The manufacturing or service delivery function is faced with bundling challenges of orders and is also involved in the demand planning process. However, due to the necessary focus, this study concentrates on bundling requisitions by buyers, comparing and contrasting it with product bundling by their counterparts in B2B marketing functions.

2.2 Bundling problem

The field of economics was the first discipline to analyze optimal bundling policies and success factors (Adams and Yellen, 1976). Marketing researchers examined how items can be aggregated into bundles to create better offers to customers and the use of bundle pricing is a common marketing practice (Garfinkel et al., 2006). This work defines bundling also known as lotting, aggregating, or combining in the B2B context as the aggregation of two or more products or services by the buyer into a bundle as part of a request for quotation or joint negotiation. Bundling can occur for a one-time purchase such as production machinery as well as regularly purchased items such as raw materials in short- and long-term periods (Schoenherr and Mabert, 2006). It is closely connected with the supplier selection problem that is aiming to select the supplier with the highest value proposition, whereby previous research has applied different techniques to consider product bundles but also capacity constraints (Wu et al., 2009), i.e., to design bundled auctions (Schoenherr and Mabert, 2006). Overall, the bundling literature is fragmented and has many facets, whereby no work was identified that attempts to summarize, compare, and contrast the different approaches from both sides of the coin. While some aspects are more relevant for the marketing side and others for the procurement side, the underlying concepts are often similar and simply called differently.

Whereas a small business might only have one employee managing all purchases, procurement in larger organizations is typically set up in a way that one specialist team deals with similar requisitions and suppliers (Monczka et al., 2020). As often as not, for instance in the case study company, each team records upcoming tenders in a manual sourcing plan. In addition, there is often no automatic data exchange, and communication across many different stakeholders is inherently slow and complicated. Therefore, the cross-potential is not visible and only become evident in the final decisions' committees, often too late to achieve further cost savings. Bundling opportunities are sometimes identified accidentally by highly skilled and well-connected buyers. For them, the bundling generator might be a useful tool to identify saving opportunities augmenting their skills and expertise (Raisch and Krakowski, 2020).

On the seller side, typically key account specialists facilitate the consistency of the offers across the worldwide marketing organization (Kotler and Armstrong, 2018). Lead buyers are a similar concept of the buying organization for which the bundling generator might be a viable tool as well. At IBM, a B2B recommender system was built matching company clients to company products. The pairing is based on co-clustering principles and helps reveal potential future demands (Vlachos et al., 2016). This approach although based on a different computational method was the most similar approach found in literature as it generates potential sales bundles, evaluates their potential value, and then ranks them based on data as leads to the salesforce even with a textual interpretation of how they were created. It was piloted in Germany leading to over two hundred sales opportunities within one year and a conversion rate of ten percent (Vlachos et al., 2016). This marketing study was taken as inspiration to build a similar artifact in the purchasing domain. In sum, bundling is a relevant topic at the purchasing-marketing interface that requires analyzing product and demand characteristics but also process capabilities, capacities, and supply chain flexibility (Ozkul et al., 2012).

2.3 Sourcing with bundling

Sourcing with bundling has been researched by various ankles and decision parameters, e.g., mixed-integer linear programming (Sarkis and Semple, 1999). Previous studies have shown that bundling in procurement may generate more than ten percent further savings (Schoenherr and Mabert, 2006). In supply chain literature, there is related research on spend analysis that can be drawn upon. This is one of the key methods that procurement organizations typically use to proactively identify savings opportunities, manage risks, and optimize their organization's buying power (Sammalkorpi and Teppala, 2022). Spend analysis aims to understand past purchases whereupon future spending for supplies and services are derived (Rendon, 2005). So-called spend cubes can be created, where the data is projected as a multidimensional cube typically in three dimensions with suppliers from whom it is bought, projects for whom it is bought, and categories of requisitions of what is bought. Operational data is first extracted, transformed, and transferred into a data warehouse, whereupon online analytical processing can be performed through a graphical representation for the users (Sammalkorpi and Teppala, 2022).

Established tool providers are, for instance, Jaggar, SAP, and Sievo which are currently expanding their capabilities with AI capabilities (Vollmer et al., 2018; Allal-Chérif et al., 2021). They deploy so-called recommender systems, which support users to find relevant information by aggregating and analyzing data through collaborative filtering and content-based filtering (Park et al., 2011). They can support decision-making, for instance in defining the ideal bundles by declaring a list of pre-existing constraints that can be tuned and prioritized (Reyes-Moro and Rodríguez-Aguilar, 2004). In recent years, those have become widely applied to make recommendations for individuals predominately in the B2C area. However, the number of use cases in B2B settings is limited so far (Zhang et al., 2017). The main challenges of recommender systems include the availability of data especially for new clients with no previous business interactions, offering complexity as well as multiple data type integration and scalability (Zhang and Wang, 2005). The shortage of data creates the necessity for models to utilize information that is not directly related to an object but must be inferred from it.

Procurement planning is the process of identifying and consolidating requirements with determining the timeframes when they are required. It is an essential part of strategic sourcing (van Weele, 2018); yet no study was identified that focuses on using this information as another input factor for generating possible bundles next to the classical analysis of historical purchasing spending. In addition, no current technological solution is known to the authors that can readily work with procurement planning data, which is largely unstructured and unstandardized. This may be due to issues dealing with uncertainty and small data sets, which may have been offset today by advances in learning mechanisms based on little information (Qi and Luo, 2020). Bundling requisitions together for greater volume increases the buyer's bargaining power, and helps the supplier offset more fixed costs, increasing the attractiveness of the business, and reducing the purchase price (van Weele, 2018). In addition, bundling usually results in fewer suppliers providing more items enabling the buyer to manage and develop on fewer external partners (Ozkul et al., 2012). However, combining requisitions takes more upfront effort to classify items into groups that are appealing to suppliers as well as technically feasible than simply buying different components separately (Schoenherr and Mabert, 2006). Other difficulties include that potential providers may lack the skills or capacities required for all the bundle's components, necessitating either major investment or subcontracting with a third party. Yet, in general, potential suppliers are more willing to competitively bid on less attractive opportunities when combined with more attractive items in a higher-volume bundle (Ozkul et al., 2012).

3. Methods

A prototypical implementation of an AI-based bundling generator is described that is currently conducted in a case study in the automotive industry. The goal is to empirically identify saving potentials by bundling requisitions, i.e., in indirect contexts such as development services. Data can be merged, for instance from tendering systems and manual planning tools along with the three dimensions of projects, components or services, and suppliers visualized in the Figure below with a one-dimensional example each.

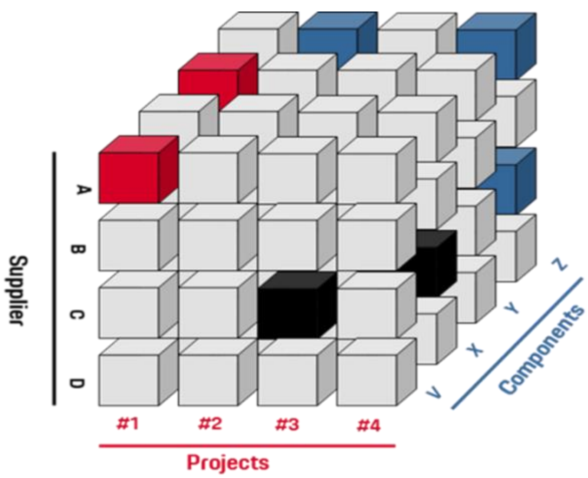

Figure 1. Bundling generator (own illustration).

The recommender system takes as input purchase order and sourcing planning data in different formats from across the organization and generates options to bundle similar requisitions, continuously learning through feedback. This can visibly increase the plannability and transparency of bundling opportunities making their saving potential tangible to management, buyers, and involved stakeholders.

3.1 Theory

Design science research in purchasing and supply management research is still underrepresented but is gained momentum (Stange et al., 2022). It is a problem-solving paradigm that strives to advance knowledge via the production of novel objects that address problems and enhance the environment in which they are instantiated (Peffers et al., 2007). Thereby, it applies the knowledge acquired to resolve issues, alter, or enhance current solutions, and produce new information, insights, and theoretical justifications (Hevner et al., 2004). The design science process is composed of six activities illustrated in the Figure below. First, identifying the issue and motivating the necessity of a solution. The second step is to specify the goals for the study. Third, the creation and design of artifacts that can be constructs, models, or methods. The fourth step is employing instantiations to resolve the issue as in this work by a case study. Fifth, evaluate the solution by contrasting the goals with the outcomes that are experienced when using the artifact. The final step is the communication of the issue as well as the artifact and its value.

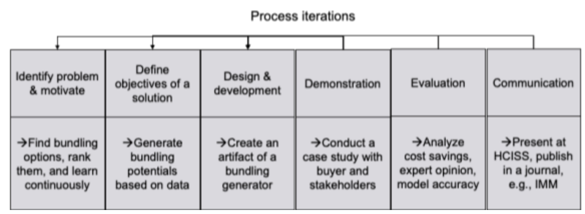

Figure 2. Design science iterative approach (own illustration based on Peffers et al., 2007).

Organizations deploy information-processing activities that best address the amount and type of information asymmetry they are faced with (Bode et al., 2011), i.e., gathering, processing, and communicating information. Information processing theory distinguishes between information asymmetry - uncertainty (lack of information) and equivocality (ambiguity of information). While gathering more data may help mitigate information uncertainty (Bode et al., 2011), addressing equivocality can require cognitive skills to transform data by logically organizing and presenting data (Aben et al., 2021). The uncertainty stems from the complexity of the environment and the frequency of changes due to various environmental variables. Typically, organizations have two strategies to cope with uncertainty and increased information needs: Firstly, organize buffers to reduce the effect of uncertainty, and secondly, design structural mechanisms and information processing capabilities to strengthen the information flow and thereby reduce uncertainty (Galbraith, 2014). This works attempts to contribute to the second path by providing data-driven actionable insights to the responsible buyers and stakeholders.

3.2 Approach

Possible bundles can be generated by first preprocessing the mostly textual data by, e.g., by generating word embeddings, where a word is represented by a sequence of numbers (Lilleberg et al., 2015). In some instances, it can be useful to singularly consider bundling opportunities on one dimension to focus the analysis particularly on this dimension. However, combinations across dimensions are common and may have a larger potential as more and sometimes surprising combinations can be identified.

Experienced buyers can determine the feasibility of the generated bundling options through an analysis of the requirements in alignment with stakeholders such as the requestor, quality and controlling functions. Thereby, many potential bundles are likely infeasible due to time constraints either due to project urgencies or because they lay too far apart. The second may be remedied at least partly by utilizing planning data and working with the stakeholders to either create long-term framework contracts or adjust requirement timeframes to create additional synergies between different business owners. In addition, the options can be ranked according to their likelihood and savings potential. The potential savings can be determined based on the planned volume, cost target, and other factors multiplied by their likelihood based on the model's confidence in the clusters.

If bundling might be feasible, negotiations may be conducted, and the results used for continuous learning to better assess the options. Thereby, human-AI collaboration has shown better performance compared to humans or AI only (Schuh et al., 2022). Next to cost savings, the increased communication between the teams might lead to further learnings of the involved employees, best practice sharing, and process improvements. However, this approach requires transparency within the organization to succeed and openness to share information, openness for joint negotiations, and ultimately the openness to share the savings.

3.3 Algorithms

Determining the best performing model to use for creating the clusters is an essential step for the quality of the generator. Since it was not possible to retrieve data that was already bundled or label the existing data, five unsupervised clustering models were trained in the case study: K-means, Mini Batch K-means, Affinity Propagation, Mean Shift, and OPTICS.

K-means clustering algorithm is an iterative technique that seeks to divide the dataset into well-defined, unambiguous clusters in which each data point only belongs to one group (Haraty et al., 2015). The clusters are kept distinct while attempting to make the intra-cluster data points as similar as possible. It allocates data points to clusters to minimize the sum of the squared distances between the data points and the cluster centroid (Wagstaff and Cardie, 2000). The data points inside a cluster are more homogeneous when there is less diversity between them. Due to its ease of usage, K-means is frequently employed as a baseline model. K-means may be computationally faster with a greater number of variables than other clustering methods, and it scales to big data sets (Coates and Ng, 2012). However, it has several drawbacks including the inability to forecast the ideal k-value, sensitivity to outliers, and poor performance with clusters of various sizes and densities.

The next algorithm investigated was Mini Batch K-means. Its fundamental concept is to employ short, fixed-size random batches of data that can be stored in memory. The clusters are updated using a fresh random sample from the dataset in every iteration, and this process is continued until convergence (Newling and Fleuret, 2016). Each mini batch applies a learning rate that decreases with the number of repetitions, updating the clusters using a convex mix of the values of the prototypes and the data. The amount of data that is assigned to a cluster during the procedure is inversely correlated with this learning rate (Feizollah et al., 2014). As the number of iterations increases, the effect of new data is reduced, therefore convergence can be detected when no changes in the clusters occur in several successive iterations (Xiao et al., 2018). When grouping large datasets, Mini Batch K-means might be used instead of the K-means.

Another algorithm used was Affinity Propagation, where the similarities between data points are used as the input for this exemplar-based clustering technique, which results in a set of exemplars and the assignment of data points to the most suitable exemplars (Frey and Duek, 2007). The data points that most accurately depict the data are referred to as exemplars. It generates clusters, which are insensitive to initialization and have converged to the neighborhood maximum using the maxproduct belief propagation technique across the factor graph. For non-sparse issues where all feasible similarities are computed, Affinity Propagation's computational and memory requirements grow quadratically with the number of data points instead of linearly with the number of input similarities (Wang et al., 2008). Affinity Propagation has been shown to find more effective clustering solutions than other methods in a shorter amount of time in several applications from fields like computer vision and biology (Wang et al., 2013). This algorithm was chosen because it does not require setting a specified number of clusters, in contrast to other conventional clustering techniques. It is also a quick clustering procedure, especially when there are many clusters (Wang et al., 2008). Some of its other advantages include being efficient, and insensitive to initialization as well as that it can find clusters with fewer errors than k-centers.

The popular mode-seeking technique Mean Shift iteratively locates the modes in the data by maximizing the kernel density estimate. Mean Shift can be a powerful resource for spotting clusters with arbitrary shapes because it is non-parametric and may be used for any set of data. This algorithm was chosen as it does not need to make any model assumption like in K-means since the number of modes detected automatically determines the number of the clusters (Carreira-Perpiñán, 2015). Additionally, it simply requires the parameter bandwidth, which serves as an automatic cluster count as well. Replacing each item with the mean of its k-nearest neighbors also solves the issue of sensitivity to outliers and effectively nullifies the impact of outliers before clustering without the need to know the outliers themselves. Additionally, it recognizes anomalies based on distance-shifted data. However, although accuracy can be achieved, its computational cost is expensive even on moderately large data sets (Yuan et al., 2012).

Lastly, OPTICS (Ordering Points to Identify the Clustering Structure) is a hierarchical density-based data clustering technique, which finds clusters of any shape and removes noise by utilizing thresholds for reachability that may be adjusted. OPTICS is closely related to DBSCAN (Density-Based Spatial Clustering of Applications with Noise). It can discover clusters of any shape and size even if databases contain noise and outliers. It finds a core sample of high density and expands clusters from them (Khan et al., 2014). Unlike DBSCAN, it keeps a cluster hierarchy for a variable neighborhood radius. Better suited for usage on large datasets (Breunig et al., 2000). One of its advantages is handling the challenge of finding significant clusters in data with different densities which is one of the main weaknesses of DBSCAN. Furthermore, like Mean Shift it is not dependent on a predetermined quantity of clusters.

4. Case study

The case study is based in the automotive industry with a recently established organization in Germany with an annual spend of about $ 3 billion that does not yet have strong tool support or data maturity in general, particularly in the procurement function. The main goal of the organization is to build an operating system with a common system architecture for all vehicles of its group and is open to other automotive manufacturers in the future. Thus, it has a wide range of purchasing requisitions that are subject to relatively much change and uncertainty for a large organization. Several buyers and stakeholders of the focal company were involved at different stages of the case study.

To propose possible bundles to the buyers, the mostly textual information first had to be preprocessed. So-called word embeddings were generated using Word2Vec which was chosen due to the ease of explainability and shortage of labeled data. Afterward, instantiations of the generator have been created using five different clustering algorithms and compared to each other to be able to determine, which algorithm is the best fit for the task. The generators are evaluated based on the opinions of experts from the procurement field that focus on bundling and the use of AI that labeled the possible bundles. They were given one of three labels: high confidence, medium confidence, or low confidence. A bundle with high confidence is a bundle that the professionals consider a high-quality bundle. A bundle with medium confidence is of less quality, and a bundle with low confidence is the least quality of all. In the final step in the research so far, each bundle is given a score based on the confidence assessment of the experts and their potential savings were determined due to a conservative assumption that two percent savings can be achieved based on previous studies on bundling effectiveness (Schoenherr and Mabert, 2006). The options are then ranked, where the highest scoring bundles appear first to the buyer. As an extension, feedback from the field may be considered to provide further feedback for general model development and specifically its confidence in the created options as well as to better approximate the potential savings improving the ranking for the buyers (Farida, 2022).

4.1 Gathering data

The data exploration began with initial data collection and continued with performing activities to be familiar with the data. This is achieved by describing and exploring data in terms of the number of attributes and records in the dataset, their data type, and any other characteristic of the data. The dataset consists of data regarding completed purchase orders with all the information related to them as well as requisitions that are either still in the sourcing process or planned in the future. The data of past requisitions was retrieved from an enterprise resource system and the data of future requisitions from a planning and budgeting tool. In total, it consists of 751 requisitions with over 30 attributes having some missing or incomplete data entries from April 2021 to August 2021 and a volume of over $ 350 million across all spend categories. The Table below shows a description of the most relevant attributes:

Table 1. Description of attributes (Farida, 2022).

Name	Definition
Shopping Cart	A unique ID number for each shopping cart
SC Creation	A date of when the shopping cart was created
Shopping Cart Value	The approved budget for all items in the cart
Shopping Cart Status	The final status of each shopping cart
eClass	The standardized category of the items
Product Description	A brief description of the items inside the cart

The next step was to concatenate the data from different sources, filter the attributes, and choose only those relevant to the artifact's goal. The reasoning behind the choice was discussed with the experts from the case study company. The data were further processed to be used directly by the algorithms. While for the categorical and numeric values some minor operations were sufficient such as changing datatypes or the format of the dates in SC Creation, the textual data needed most of the preparation. First, all texts were converted into the same language for clustering. A translator library (Yin, 2014) was used to identify and translate some of the textual information from German to English, removing stop words, and finally stemming and transforming them to lowercase. Before clustering, word embeddings were generated for the Product Description and eClass attributes using Word2Vec (Gensim, 2022), which is one of the most widely used techniques to learn word embeddings using a two-layer neural network. It is transforming natural language to be computer-readable so that mathematical operations on words can be applied to detect their similarities. The Word2Vec model was trained with a vector size of 100, then document vectors were generated. Since the model generates numerical vectors for each of the words in a document, one must find a way of generating a single vector out of them. Since the attributes Product Description and eClass contain relatively short texts, the average of vectors was used.

4.2 Processing models

The next step was determining the model to use for creating the clusters. The five algorithms discussed in the previous section were implemented. First, K-means and Mini Batch K-means, the value of k or the number of clusters was determined using a popular method known as the elbow method, which plots the various values of cost with changing k. As the value of k increases, there will be fewer elements in the cluster. Therefore, the average curve will decrease, and the lesser number of elements means getting closer to the centroid. So, the point where this curve declines the most is the elbow point (Bholowalia and Kumar, 2014). Using this method, the number of clusters created using both algorithms was 110.

Next, the Affinity Propagation model was fitted with damping as the extent to which the current value is maintained relative to incoming values of 0.94. The rest of the values used were the default values set by Scikit-learn. The next algorithm is the Meanshift algorithm, which only takes one attribute as an input, which is the bandwidth attribute. To determine the value of the bandwidth, the estimate-bandwidth function from Scikit-learn (Scikit-learn, 2022) was used with the default parameters except for the quantile parameter, which is set to 0.5 meaning that the median of all pairwise distances was applied.

4.3 Communicating results

Of the five algorithms, Mini Batch K-means had the best performance with the most uniform and consistent generated options, while Mean Shift was the worst performing algorithm. Not sufficient data was the main factor for some of the algorithms not performing well. Yet, the data of future requisitions could be handled well as another input next to the data of past requisitions. As outlined in the methods section, the developed model will be continuously improved through supervised learning when labeled data are available by using feedback on the generated options by the buyers of the case study company.

The model's confidence in the cluster seems to be a good indicator of the bundling likeliness; however, time constraints are a challenge as the buyers reported that project time pressure and different project schedules are their main challenges in practice to bundle demands. The dates of the attribute SC Creation had the second highest weight for determining the clusters of Mini Batch K-means. After discussing the results with the buyers, a ninety-day threshold was defined for further model development. In addition, just like the recommendation engine employed by IBM for salespeople, a textual interpretation of why the clusters were created may additionally strengthen their accountability.

If the prototype is well received by the buyers, management, and other stakeholders, the design science approach could be extended with an action-based intervention study to validate the business case whereby realized savings and infeasible bundles will likely be helpful feedback next to the expert's initial confidence assessment. In addition, procurement organizations can show the value of procurement planning activities leading to better input data. This may further strengthen its impact leading to better recommendations and more savings. The bundling generator could become an integrated part of the sourcing system, where for example the Volkswagen Group already deploys machine learning algorisms to suggest to the buyer other possible suppliers in the context of indirect procurement (Hülsbömer, 2019).

5. Conclusion

With this study, we intend to contribute to literature and practice in three ways. First, theoretically in terms of adding to the bundling problem using information processing theory in an automotive case study. This pertains in particular to the literature on spend analysis that has mostly been looking backward using spend data from purchasing orderings and invoices to infer saving potentials in the future. To the knowledge of the authors, this is the first study to combine historical data with forward-looking procurement planning data, which has the inherent challenge that it cannot be as information-rich and precise as historic purchases. While this may have been a limitation in the past, literature and this case study show that this is not necessarily true anymore.

Second, an artifact of a bundling generator has been created using the design science research approach. The developed artifact is not only of interest to the case study company but also to analytical tool providers whereby the generator may either expand sourcing solutions or analytical frameworks of the spend cubes with forward-looking planning data. Technology providers could expand their capabilities by enriching historical data to provide more value. In addition, procurement planning is a strategically relevant tool for procurement organizations, to proactively manage demand. While for direct procurement, there are often very detailed cross-functional demand forecasting procedures in place, for indirect procurement many organizations struggle to achieve high-quality data with their stakeholders. The bundling generator might provide an additional argument to commonly define high-quality planning data on future requisitions as the value to the functional departments can be shown in terms of savings and increased planning security, e.g., by deducting framework contracts with key suppliers.

Third, the literature on bundling was reviewed from the perspective of the marketer and the buyer respectively showcasing the potential to approach a common problem from other sides of the coin. While relevant solutions exist for purchasing and marketing respectively, there is still research potential to provide better solutions for buyers and marketers to make use of the available data. This research builds on the study by Vlachos et al. (2016), where a B2B recommender system was built to assist marketers in a similar way as buyers in this study. In general, more research on B2B recommendation engines is needed in terms of their potential applications and effects on performance and other aspects.

As in every study, there are important limitations. As a single company case study, more research must be conducted to generalize the results. This could be mitigated in part by using the artifact in other organizations within the same group or being applied by a technology provider in diverse settings. Another way to further improve the results could be to try using some supervised algorithms using the labeled data that came from the results of the experiments performed. In addition, Word2Vec proved useful in this context despite criticism as being outdated. Yet, other techniques such as Fasttext based on a more granular level with character n-grams (Salur and Aydin, 2020) may further improve the results. Lastly, design principles through the lenses of the information processing theory can be deduced in more detail during the further evaluation of the case study.

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