Quality of Artificial Intelligence Driven Procurement Decision Making and Transactional Data Structure

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ABSTRACT

Purpose: Current data driven decision making development calls for the quality assurance based on quality data structure. The paper analyses transactional data structure used in public procurement in Slovakia and the effect of data structure enhancement on prediction performance as crucial part of artificial intelligence (AI) quality assurance standard. We examine the significance of data structure enhancement and attributes transformation for prediction modelling.

Methodology/Approach: The research is based on mutli-step model using stacked ensemble machine learning (ML) algorithm and simulating input space of 211 attributes transformed and aggregated according to different perspectives assessed by r^2, mean absolute error (MAE) or mean square error (MSE).

Findings: The results show that different performance of variable categories to prediction power. The most significant predictors were in category related to sectoral product classifications and in category related to variables aggregated for supplier, what underline the significance of structured information of all suppliers and negotiation participants in public tenders.

Research Limitation/Implication: Methodology is based on big data with high complexity. Due to limited computing power, no subjects' IDs were used as inputs. The complexity behind data and processes call for more complex simulations of all variables and their mutual interaction and interdependencies.

Originality/Value of paper: The paper contributes to data science in transactional data domain and assessed the significance of different variables categories with respect to their specific added value to prediction power.

Category: Research paper

Keywords: transactional data; public procurement; prediction; data structure; machine learning

1 INTRODUCTION

The digital transformation transforms purchasing and supply management (PSM) and brings new challenges not only in digitising documents and processes but nowadays mainly in the fields of data driven decision making, expert systems or automation of procurement decision making (Bodendorf, Hollweck and Franke, 2022). Current approaches contributing to PSM research lie in the selection of suppliers, calculation of equilibrium prices, sourcing and negotiation strategies, risk supplier management and many other.

As this research is focused more on elements sourcing strategies, we are using the definition by Giunipero et al. (2019), who defines sourcing as the process of fulfilling organizational buying needs by managing a supply base through strategic and transactional interactions with suppliers in alignment with corporate goals. As sourcing decisions have a major impact on corporate success it is necessary to study particular elements of whole sourcing process. Giunipero et al. (2019) in his literature survey found, that the most frequent domain of sourcing related studies was focused on transaction cost and e-procurement was the most frequent sourcing tool in his sample of articles. One element of this transformation is focused on procurement processes automation and related data services, where data plays crucial role to achieve high quality automation services or any expert systems and data-driven decision making (Krcmar, 2015).

One direction of digital transformations within procurement are big data and predictive analytics. Predictive business analytics is a way how to improve future predictions (Maisel and Cokins, 2014) or support development of more precise and quality automation tools like bots which need to incorporate predictive techniques and quality data to be efficient as expected by procurement managers (Omar et al., 2021; Viale and Zouari, 2020; Van Hoek, Larsen and Lacity, 2022).

Within the rise of artificial intelligence (AI) driven solution dealing with automated data service or data-driven decision making or human action, key performance indicators (KPIs) for assessing the quality and performance are recommended. KPIs may vary substantially from application to application but include mainly processing and reconstruction tasks, safety, performance, match with the target use case, usability, ethical aspects, and price. (Bosmans, Zanca and Gelaude, 2021). For this purpose, quality assurance is necessary to assure that the AI application operates over time as expected dealing mainly with segmentation, anomaly detection, classification, monitoring, prediction or decision making/human action support.

To develop standards from this context, currently several initiatives emerged on government or industrial level. E.g., UK Government published their own strategy or roadmap to an effective AI assurance ecosystem, which sets out the key steps, and the roles and responsibilities required to develop an effective, mature AI assurance ecosystem (CDEI, 2021).

On the other hand, some standardisation incentives emerged also from quality management community, e.g. Consortium of Quality Assurance for Artificial-intelligence-based products and services which proposed Guidelines for the Quality Assurance of AI Systems to reduce the quality risks of AI products and to investigate and systematize quality assurance technology for AI products, and conduct research and development for us to live a safe and secure life, society, and economy (QAI, 2020).

All those initiatives have similar objectives although partially different key approaches or crucial points. Generally, all initiatives mention data quality and performance quality issues, where additional quality properties of AI components and AI-based systems have to be taken into account. Zhang et al. (2020) consider the quality properties in correctness which refers to the probability that an AI component gets things right, model relevance measures, robustness, security measures, data privacy, efficiency measures, fairness and interpretability.

Felderer, Russo and Auer (2019) highlight the additional importance of data quality. According to ISO/IEC 25012 (ISO/IEC, 2008), data quality lies in inherent data quality related to specific data domain values and possible restrictions, relationships of data values and meta-data and in the system-dependent data quality dealing with data quality level when data is used under specified conditions.

Generally, we agree with Bosmans, Zanca and Gelaude (2021), that testing of AI components or AI-based systems refers to any activity aimed at detecting differences between existing and required behaviours of AI components or AI-based systems. Although, the testing properties (such as correctness, robustness, or efficiency) is very sensitive to the quality characteristics defined before. Although, the performance of AI is explained by the receiver operating characteristic (ROC) curve or confusion (coincidence) matrix or the amount of time saved if the aim is a better workflow or process it is not a simple context. It strictly depends on decision type, end user expectation and discrimination policy in prediction performance like false positive acceptance (different views on confusion matrix usage).

According to Felderer and Ramler (2021), a wide range of challenges exists as we observe a lack of (standardized) approaches for quality assurance of AI-based systems and the understanding of the problem is still very incomplete, e.g. the phenomenon of adversarial examples.

To contribute to the developing quality assurance of AI services development, we are focusing on one specific issue following challenges mentioned above which is not mentioned within data quality specifically and from our point of view it is crucial point of the CRoss Industry Standard Process for Data Mining (CRISP-DM) steps and Guidelines for the Quality Assuranceof AI Systems (QA4AI) approaches – quality of data structure. This crucial point is part of validation data and test input generation problems mentioned by Felderer and Ramler (2021) and is very sensitive in transactional data area. Within this paper, we are trying to present importance of transformation of transactional data issue as input space preparation to fulfil higher accuracy and correctness measures.

The integration of the high-quality data in the transactional model requirement goes in line with predictive procurement systems standards emergence (Folmer, Luttighuis and Van Hillegersberg, 2011). "Master data" from Business-to-Business (B2B) networks include supplier master data, historical transactions, financial identification, accounting data and data like company size, industry, geographical localization and risk related data. These data require some form of sharing between participants of the network to be able to provide aggregated data services and information, including predictive procurement insights (Ohm, 2014). Due to perceived sensitivity of some transactional data, they are often provided to the market in anonymized or aggregated form to provide indicators from different perspectives, macro-level (information on commercial activities in industries, geographies, and markets) or micro level (behaviour of specific supplier).

The insight into the data structure and type provided by transactional data repositories was assessed by (Gruenen, Bode and Höhle, 2017). The main documents and attributes mentioned in procurement processes were Quotes, Sales order, Purchase order (PO) (including PO change revisions), Contracts, Advanced shipping notification, Goods receipts, Invoice, Payment.

As all these attributes are based on different quality and range within each business platform and are sensitive to the functionalities and character of the procurement, the suitable data structure is crucial for predictive analytics purposes. That's why, this research is focusing on data structure within public procurement, where predictive analytics was not so frequent in current studies, and it is more related with policy documents describing product and services category classification systems and procedures permitted by legislation in the country (European Commission, 2017). On the other hand, raw and transformed data structure are crucial for improving quality of innovative data services, esp. in prediction or classification related data services.

2 METHODOLOGY AND DATA DESCRIPTION

As mentioned above, current developments in digitisation of procurement processes have supported creation of several business platforms allowing to centralise in different forms transactional data aggregation of procurement transaction within all procure-to-pay phases. In other words, it contributes to data sharing, data aggregation and data transformation for development new generation of data services. These data services and related research behind are facing new challenge – data quality in line with suitable data structure.

Our research is using transactional data aggregated from public procurement in Slovak Republic, specifically from platform Electronic contracting system (EKS) (EKS, 2022) as open data platform providing possibility to download and analyse wide range of transactional data. Our research objective is to provide insight into the opportunities of different data structure based on data aggregation and transformation for improving specific prediction tasks – prediction of procurement performance. In our case, as product and classification schemes is not so ideal within this platform, instead of product price we are considering savings as predicting parameter within this research. On this example, we would like to analyse added value of different data structure levels contributing to increasing predicting power of data models or potential data services.

The main methodology of the paper is based on understanding core data structure provided by EKS platform and through data aggregation and transformation to enhance data structure from the view of different decision-making tasks and examine, how enhancing core data structure will affect machine learning based prediction model. Prediction model will be selected as a best model from wide range of machine learning models/algorithms. To better describe the methodology, we have to describe the functional specifics of EKS platform, data structure enhancement approach and prediction algorithm selection.

2.1 EKS Description

EKS platform (generally developed for not complex products and services) is web-based platform providing opportunities for public procurers to publish their public tenders, to search suitable suppliers, to negotiate contractual conditions and report tender's results. For suppliers it offers possibilities to be notified about related tenders published by public procurers and respond on tender calls. The main sourcing related functional specific is based on product classification scheme integration – Common Procurement Vocabulary (CPV) (Common procurement vocabulary, 2012). Although, there are specifics how CPV are able to be used by public procurers when publishing tender or suppliers within notification feature. Public procurers have free hand to select different CPVs related to the tender. It means, they can select one or more CPVs on different levels, e.g. one CPV on highest level (2nd level as highest and widest category of product like "Agricultural, farming, fishing, forestry and related products" with code 03). Not all CPVs were used, and different product domains have different depth of classification. Generally, the most precision level of classification is eight level, e.g. lentil with the code 03212211-2). Not all CPVs are used. On the other hand, suppliers, when registering on the portal, are able to set up concrete CPVs on different levels for notification purposes. It means, the system will notify all related suppliers on exact CPV level and below, e.g. if someone has set up notification on CPV 2nd level for example 03, this supplier will be notified also when tenders with CPV lower levels will be published, for example also tender with CPV code 03212100-1. After publishing tender, all relevant suppliers are notified but of course only some of them may respond. Tenders are transparent and provide possibility to choose between transparent request for quotes or electronic English auction. All suppliers with an interest are able to send their price offers or change them.

2.2 Data Structure Description and Methodological Approach

Data structure open for downloading and API defines data set related to public procurement process on EKS platform, although some data are not provided (less important and minority of data).

To explain our approach to data structure enhancement for modelling purposes, we have to understand raw structure of data, which is the base for transformation of data into new indicators. Short explanation of each attribute is given in the Table 1. On the base of these raw attributes, transactional data offer an opportunity to calculate other interesting indicators by aggregating or cumulating principles (according to time or subject) or indicators like for example success rates. These transformations/aggregations are realized within different attributes from raw data structure and we are providing the most important aggregations within:

- contracting authority (CA) (public procurer), to understand aggregated statistics of public procurer and his performance and practices within all tenders published;
- contractor (CO) (winning supplier), to understand aggregated statistics and behaviour of concrete CO and all his tender participations;
- all contracts between specific CA and CO (COCA) (to understand evolution of statistical indicators in time within all contracts between one CO and CA);
- all applicant clusters within tenders (ncomb) (where applicant is a company offering and negotiating within a tender and ncomb provides an information about composition of suppliers within specific tender). Ncomb is aggregated also from different perspectives of other attributes like ncombCA, ncombCO, ncombCOCA…;
- CPV and combinations with previous dimensions (aggregations only within one category of product and services as a whole or within different perspectives like CO_CPV, CA_CPV, COCA_CPV, ncombX_CPV) to assess behaviours and statistics within particular product category as different market segments have different specifics.
- Within CPV definition we have calculated also an attribute cpvlvl, where it defines CPV level depth or in other words, how specific is the tender described and defined within CPV levels (this is important for assessment, how efficient sourcing or searching for suitable suppliers is).

Of course, within other business platforms, there could be also other types of attributes/data, e.g. type of negotiation (ERMMA, NIPPON…), ratings, financial performance of suppliers and other types of timeframe related transformation.

Table 1 provides basic explanation of data structure and data transformation.

Table 1 – Basic and Enhanced Data Structure Approach

Raw data structure	**Explanation**	**Aggregation dimension**
Procedure type Procurer organisation type Contract type EU funding Number of notified suppliers Applicants Estimated/Final value amount	Type of public tender according to procedure defined by legislation Type of public procurer According to goods, services or work If the tender is financed from EU grants Number of potential suppliers notified within the EKS system Number of applicants in negotiation Estimated/negotiated value of contract	
Transformation and aggregation		
Contracts_count Contracts_sum Contracts_mean Contracts_SD Savings_mean Savings_SD NumOfBids_mean NumOfBids_median NumOfBids_SD NumBidPerCOs_mean NumBidPerCOs_median NumBidPerCOs_SD	Number of contracts Total value of contracts Mean of contract's value Standard deviation of contract's value Mean or standard deviations of savings achieved within tenders Mean, median or standard deviation from number of bids within tenders of all applicants Mean, median or standard deviation from number of bids within tenders of winning contractor	CO, CA, COCA, ncomb, ncombCPV, ncombCA,ncombCA_CP, partially ncombCO
Applicants_mean Applicants_median Applicants_SD	Mean, median or standard deviation from the number of applicants within tenders	CO, CA, COCA, CO_CPV, CA_CPV, COCA_CPV
CountCumul SR	Number of tender participations Success rate	CO
DependencyCA DependencyCO Interdependency first_cpv_lvl first_cpv2 nunique_cpv2_in_contract nunique_cpv3_in_contract num_of_cpv_in_contract num_of_cpv_no60_in_contract nunique_cpv2_no60_in_contract nunique_cpv3_no60_in_contract mean_cpvlvl SD_cpvlvl	Ratio of volume supplied from particular CO on total value of all tenders by CA Ratio of volume supplied from particular CO to particular CA on total value of all winning contracts by CO Sum of Dependency CA and CO Which CPV lvl is used as the main CPV Main highest category of product or services Number of unique cpv on 2nd lvl (highest) or 3rd lvl within tenders when more items purchased Number of CPVs used within contracts Number of CPVs related with transport/logistics Number of unique cpv on 2nd lvl (highest) or 3rd lvl related with transport and logistics within tenders when more items purchased Mean or standard deviations of different CPV levels used within tender	

Total of 211 attributes were calculated and used as an input into machine learning algorithms/models. From these attributes, we have categorized transformed attributes into following categories for better visualisation of prediction performance as shown in following table.

Table 2 – Categories of Attributes within Enhanced Data Structure

Category	**Description**
C	Core – attributes from raw data structure
CO	All attributes aggregated for contractor – supplier including his aggregation according to different CPV
CA	All attributes aggregated for contracting authority – public procurer including his aggregation according to different CPV
COCA	All attributes aggregated for bilateral relation, it means all contracts between contractor and contracting authority including his aggregation according to different CPV
NCOMB	All attributes aggregated for particular cluster or composition of applicants negotiated within tender.
CPV	All attributes aggregated for tenders with specific definition or use of CPV levels within tender definition

On the base of model attributes from Table 1 and categories from Table 2, we will examine, which category of transformed attributes and enhanced data structure will provide some added value for increasing prediction power of selected prediction model.

As an output parameter, the saving achieved from the tender or negotiation was selected. Savings is the attribute most often used for negotiation performance analysis. Although, there are plenty of other potential prediction purposes like prediction of winner; prediction of applicant exclusion, etc.

2.3 Prediction Model Selection

For the prediction modelling, we have decided to select the best prediction algorithm from generally known algorithms based on all inputs from Table 1. This algorithm was then used for data structure manipulation, where several rounds of modelling were performed. In first step, only core category inputs the model, in the second round the model is enhanced by CPV category of input attributes, in third CA related attributes, then CO, COCA and finally Ncomb related attributes were added as inputs. The logic of sequence is based on general approach common in public procurement systems, where precision of category of product and services definition is the base factor for attracting suitable suppliers. Then the basic parameter is public procurer, where standard data structure offers this attribute as formal – structured way and aggregated statistics is easy to calculate. Identifications of public suppliers is not so common as many times identification of applicants is possible only through non-structured text documents. Logically we are able to enhance our aggregation by CO vs CA statistics and related portfolio or cluster of applicants expressed an interest in contract negotiation.

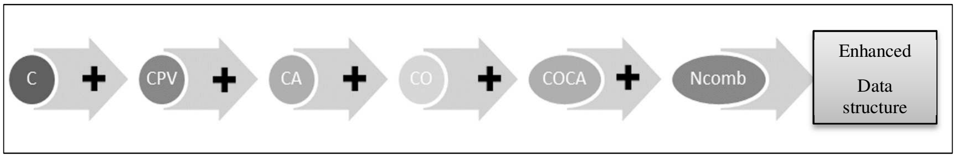

Figure 1 – Data Structure Enhancement and Transformation Approach

2.4 Data Sample

Our research was conducted on the datasets derived from EKS platform (open API) explained above with following characteristics (Table 3).

Table 3 – Sample Description

	Total	Mean	Median	St. deviation
Number of contracts	153,022			
Number of contracting authorities	4,059			
Volume of contracts		13,624.52	1779.99	37,816.30
Savings		0.15	0.07	0.18
Number of applicants		3.21	3	2.32
Number of bids per contract		28.7	9	53.62
Timeframe	1/2015 – 09/2022			

3 RESEARCH RESULTS AND DISCUSSION

According to mentioned methodology, we have calculated all attributes for enhanced data structure. These inputs were used for searching the best machine learning based predictive ensemble model. For this purpose, H2O AutoML (v. 3.38.0.4) package was used in python. AutoML as automatic machine learning tool which automates the process of training a large selection of candidate models. H2O's AutoML can be used for automating the machine learning workflow, which includes automatic training and tuning of many models like Deep Learning (NN), Distributed Random Forest (DRF), Gradient Boosting Machine (GBM), Stacked Ensembles, XGBoost and many other algorithms. For the modelling 27 algorithms were selected (80:20 ratio for training vs testing sample). The performance of all included model was calculated through importance analysis of particular model within stacked ensemble on saving prediction. Results of first ten models is presented in Table 4 below.

Table 4 – Ensemble Performance

First ten models_in_ensemble	NotScaledImp	ScaledImp	StandardImp _SumTo1
GBM_1_AutoML_6_20230106_163308	0.010	1.000	0.149
GBM_grid_1_AutoML_6_20230106_163308_model_5	0.009	0.903	0.135
GBM_3_AutoML_6_20230106_163308	0.009	0.887	0.132
GBM_2_AutoML_6_20230106_163308	0.007	0.681	0.102
GBM_4_AutoML_6_20230106_163308	0.006	0.606	0.090
DeepLearning_1_AutoML_6_20230106_163308	0.006	0.568	0.085
GBM_grid_1_AutoML_6_20230106_163308_model_4	0.005	0.555	0.083
GBM_grid_1_AutoML_6_20230106_163308_model_10	0.003	0.322	0.048
GBM_grid_1_AutoML_6_20230106_163308_model_6	0.003	0.301	0.045
GBM_grid_1_AutoML_6_20230106_163308_model_3	0.003	0.258	0.038
GBM_5_AutoML_6_20230106_163308	0.002	0.212	0.032

The stacked ensemble model was used for further analysis. Within this analysis, we applied this algorithm in several steps according to different categories of input attributes as explained in methodology section. Then different performance indicators were applied on testing sample and assessed (MAE, R^2 and MSE). Model was trained by 5-fold cross-validation.

Table 5 – Data Structure Enhancement Prediction Performance

Composition of data structure – categories of attributes as inputs	MAE_CV mean	R2_CV mean	MSE_CV mean	R2	MAE	MSE
C	0.048	0.404	0.005	0.403	0.048	0.005
C+CPV	0.045	0.459	0.004	0.462	0.045	0.004
C+CPV+CA	0.044	0.473	0.004	0.475	0.044	0.004
C+CPV+CA+CO	0.043	0.507	0.004	0.505	0.042	0.004
C+CPV+CA+CO+COCA	0.042	0.507	0.004	0.503	0.042	0.004
C+CPV+CA+CO+COCA+NCOMB	0.042	0.515	0.004	0.510	0.042	0.004

According to results, were able to achieve the best r^2 within whole input space on the 0.51%, what is relatively good result according to the complexity and achievements on such a complex transaction data. Although, the precision level is not the case. The most important result lies in the question how enhancing data structure by specific types of attributes will improve the prediction precision. The reason for this approach is to be able to assess the necessity of data related architecture and functionalities development of the business platform to provide the best performance of different types of data services.

The most important category of input attributes for prediction modelling is in raw attributes of category C. According to variable importance results, the most important variable is applicants, which is based on theoretical assumptions and experimental results from range of studies claiming the importance of competition size based on the number of competitors. According to the Table 6, this variable has more than 30% importance with a big head start and variable NcombCO_contracts_count (as a number of contracts won by specific contractor within the same cluster of applicants) more than 10%. Other importances are lower than approx. 5% and their added value is not so important solely, although as a whole in the complex model they can improve the model until 51%.

Table 6 – Predictors Importance

Variable	**Importance**	**Variable**	**Importance**
applicants	0.310314182	Ncomb_savings_median	0.028026846
NcombCO_contracts_count	0.108600275	CO_savings_median	0.02799478
CO_savings_mean	0.051634217	NcombCO_winning_ratio	0.025026742
NcombCO_VolumeCO_WinProp	0.042289431	Ncomb_CPV_savings_median	0.023726107
CO_CPV_savings_mean	0.034241151	CA_CPV_savings_mean	0.012929877
Ncomb_savings_mean	0.031519652		

Better visualisation of this added value of specific category of attributes to performance indicators, specifically r^2 and mean average error is provided on graphs below. For better understanding of the significance of specific types of attributes only categories of these attributes are visualised and for better illustration of results.

As we see, the most significant added value is category C+CPV. It means, that for every prediction or data service, category of product or market segment is very sensitive to prediction performance what support the statement, that within different category of products, there are specific suppliers possibilities to behave and to bring significant savings through their business margins. Relative improving of precision was on 14.7%. Category of product and services seems to be the most significant and important when developing business platform. It is very sensitive on the way how category functionalities are provided. There is a variety of ways how to set up CPV selections, restriction, control against correct selection or notification purposes which is very sensitive on data science results.

Next category of variables are variables related to behaviour of contracting authority as procuring organisation. The reason is based on the assumption, that each organisation has its own specifics within internal procedures, quality of procurement teams, specific focus on particular category of product etc. This enhancement improved our model absolutely by approx. 0.01% although relatively it improves precision by 2.7% against data structure C+CPV.

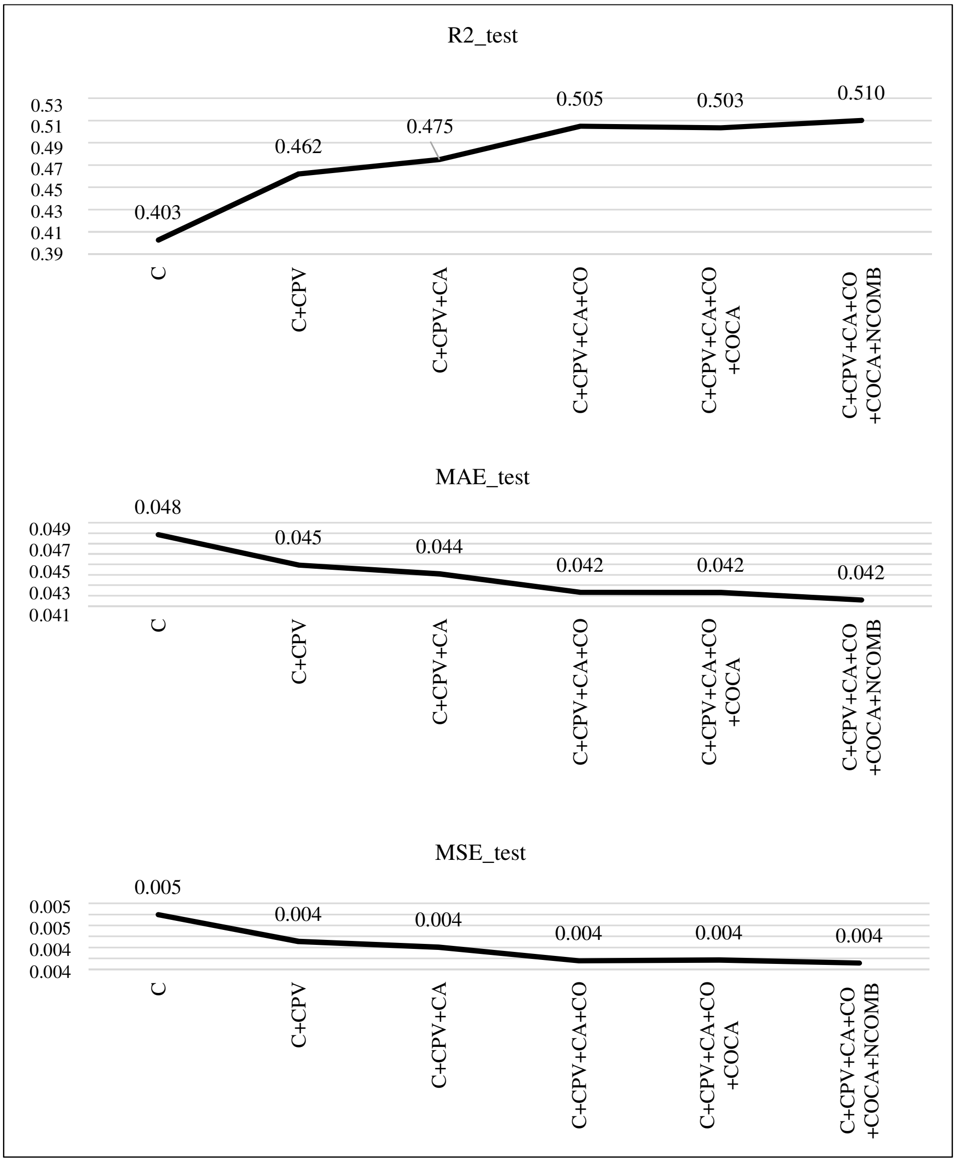

Figure 2 – Prediction Performance When Enhancing Data Structure by Specific Categories of Input Attributes

Very significant is also to understand behaviours of winners. These attributes improved the precision of the model about 6.2% relatively. It shows, that information/data about suppliers are more significant for quality data service development then information about procurers and their historical behaviour or specifics. This result can be interesting when considering the quality or structure of data given by legislation in public procurement, where generally, according to our experiences with data from different countries (e.g. in Tenders Electronic Daily (TED)), the contractor is often not clearly identified by his business identification number. It calls for legislation modification, if we would like to improve data services and data analysis but also in the context of cartel or collusion diagnostics.

Bilateral aggregation within all contracts between contractor and contracting authority doesn't bring any improvements, although it can be caused by the assumption, that if we include separately CO and CA into the input space, the information on behaviour of COCA is hidden inside the model.

The last improvement we see in the category of ncomb, where aggregation of data and calculation of related aggregated indicators provide an information about the behaviour of the applicants' cluster within the negotiation. Regarding the data structure, it means, that it is necessary to process and provide also data of non-winning applicants within negotiations as it provides additional information on potential performance impact. It can be based on specific behaviours of fixed supplier clusters or cartel agreements, or other signal and indicators related with the evolution of such a clusters. This category can improve prediction relatively by 1.4% against data structure C+CPV+CA+CO to the final value of 51% R^2.

Our results show that there is a significant importance of data manipulation or system proposition for better data services or data science purposes based on transactional data structure and related data quality. It can help decisions made by policy or market makers, where is necessary to emphasise on architecture requirements and which data should be provided in structured form to provide synergic evolution of high quality of data services based on transactional data.

4 CONCLUSION

Within this research, we focused on specific type of transactional data in public procurement area. On the example of public procurement platform EKS in Slovak Republic, we have tested different level of data structure within machine learning stacked ensemble algorithm to analyse performance of prediction model related to savings achieved from negotiations. We have transformed data from core – raw data structure into different dimensions. Indicators aggregated from CPV related data as the dimension of product category specifics show highest added value in achieving improved prediction results. Another very important category are data about suppliers/applicants (companies registered in negotiation) and related indicators describing some concentration of applicants within negotiation. Category of contractor or unsuccessful bidder data allows to calculate and process indicators related to behavioural analysis and specific behavioural patterns diagnostics which is specifically significant in public procurement, where transparency and unfair behaviour can harm efficiency of public spending.

This methodology shows only first step in transactional data structure efficiency analyses. For more complex research, it would be necessary to apply more complex approach of enhancing data structure, esp. In simulation of separate groups or clusters of indicators within one data category or between them as they have different explaining power and impact on ML results. Together, it would be suitable to enhance data structure also by other types of indicators and attributes as we were able from EKS platform like auction type, rating and other. By further research in this area, we will be able to assess the value of each attribute on systemic development of future data services against to the cost related to architecture and functional development of digital business platform.

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REFERENCES

Bodendorf, F., Hollweck, B. and Franke, J., 2022. Information asymmetry in business-to-business negotiations: A game theoretical approach to support purchasing decisions with suppliers. *Group Decision and Negotiation*, [e-journal] 31(4), pp.723-745. DOI: 10.1007/s10726-022-09780-3.

Bosmans, H., Zanca, F. and Gelaude, F., 2021. Procurement, commissioning and QA of AI based solutions: An MPE's perspective on introducing AI in clinical practice. *Physica Medica*, [e-journal] 83, pp.257-263. DOI: 10.1016/j.ejmp.2021.04.006.

Centre for Data Ethics and Innovation (CDEI), 2021. *The roadmap to an effective AI assurance ecosystem.* [online] GOV.UK. Available at: <https://www.gov.uk/government/publications/the-roadmap-to-an-effective-ai-assurance-ecosystem/the-roadmap-to-an-effective-ai-assurance-ecosystem> [Accessed 03 January 2023].

Consortium of Quality Assurance of AI Systems (QAI), 2020. *Guidelines for the Quality Assurance of AI Systems. 2020.02 edition.* [pdf] Consortium of Quality Assurance for Artificial-Intelligence-based Products and Services. Available at: <https://www.qa4ai.jp/QA4AI.Guideline.202002.en.pdf> [Accessed 03 January 2023].

Elektronický kontraktačný systém (EKS), 2022. XEKS. [online] Available at: <http://www.eks.sk/> [Accessed 02 January 2023].

European Commission (EC), 2012. *Common procurement vocabulary, Internal Market, Industry, Entrepreneurship and SMEs.* [online] Berlin: Ramboll. Available at: <https://single-market-economy.ec.europa.eu/single-market/public-procurement/digital-procurement/common-procurement-vocabulary_en> [Accessed 02 January 2023].

European Commission (EC), 2017. *Final Report: Review of the Functioning of the CPV Codes/System.* [pdf] Bochum: Cosinex GmbH. Available at: <https://ec.europa.eu/docsroom/documents/27821/attachments/1/translations/en/renditions/pdf> [Accessed 01 January 2023].

Felderer, M. and Ramler, R., 2021. Quality assurance for AI-based systems: Overview and challenges (introduction to interactive session). In: D. Winkler, S. Biffl, D. Mendez, M. Wimmer and J. Bergsmann, J., eds. 2021. *Software Quality: Future Perspectives on Software Engineering Quality. SWQD 2021. Lecture Notes in Business Information Processing*. Cham: Springer. pp.33-42. DOI: 10.1007/978-3-030-65854-0_3.

Felderer, M., Russo, B. and Auer, F., 2019. On testing data-intensive software systems. In: S. Biffl, M. Eckhart, A. Lüder and E. Weippl, eds. 2019. *Security and Quality in Cyber-Physical Systems Engineering*. Cham: Springer. pp.129-148. DOI: 10.1007/978-3-030-25312-7_6.

Folmer, E., Oude Luttighuis, P. and Van Hillegersberg, J., 2011. Do semantic standards lack quality? A survey among 34 semantic standards. *Electronic Markets*, [e-journal] 21(2), pp.99-111. DOI: https://doi.org/10.1007/s12525-011-0058-y.

Giunipero, L.C., Bittner, S., Shanks, I. and Cho, M.H., 2019. Analyzing the sourcing literature: Over two decades of research. *Journal of Purchasing and Supply Management,* [e-journal] 25(5), 100521. DOI: 10.1016/j.pursup.2018.11.001.

Gruenen, J., Bode, C. and Hoehle, H., 2017. Predictive procurement insights: B2B business network contribution to predictive insights in the procurement process following a design science research approach. In: A. Maedche, J. vom Brocke and A. Hevner, eds. 2017. D*esigning the Digital Transformation. DESRIST 2017. Lecture Notes in Computer Science*. Cham: Springer. pp.267-281. DOI: 10.1007/978-3-319-59144-5_16.

ISO/IEC, 2008. *ISO/IEC 25012:2008 software engineering – software product quality requirements and evaluation (square) – data quality model. Technical report.* Geneva: ISO.

Krcmar, H., 2015. *Informationsmanagement.* 6th ed. Wiesbaden: Springer.

Maisel, L. and Cokins, G., 2014. *Predictive Business Analytics: Forward Looking Capabilities to Improve Business Performance.* Hoboken: Wiley.

Ohm, P., 2014. Changing the rules: General principles for data use and analysis. In: J. Lane, V. Stodden, S. Bender and H. Nissenbaum, eds. 2014. *Privacy, Big Data, and the Public Good: Frameworks for Engagement.* Cambridge: Cambridge University Press. pp.96-111. DOI: 10.1017/cbo9781107590205.006.

Omar, I.A., Jayaraman, R., Debe, M.S., Salah, K., Yaqoob, I. and Omar, M., 2021. Automating Procurement Contracts in the Healthcare Supply Chain Using Blockchain Smart Contracts. *IEEE Access*, 9, pp.37397-37409. DOI: 10.1109/ACCESS.2021.3062471.

Van Hoek, R., Larsen, J.G. and Lacity, M., 2022. Robotic process automation in Maersk procurement–applicability of action principles and research opportunities. *International Journal of Physical Distribution & Logistics Management*, [e-journal] 52(3), pp.285-298. DOI: 10.1108/IJPDLM-09-2021-0399.

Viale, L. and Zouari, D., 2020. Impact of digitalization on procurement: the case of robotic process automation. *Supply Chain Forum: An International Journal*, [e-journal] 21(3), pp.185-195. DOI: 10.1080/16258312.2020.1776089.

Zhang, J.M., Harman, M., Ma, L. and Liu, Y., 2020. Machine learning testing: survey landscapes and horizons. *IEEE Transactions on Software Engineering,* [e-journal] 48(1), pp.1-36. DOI: 10.1109/TSE.2019.2962027.

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CONFLICTS OF INTEREST

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