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Development of recommendation systems to improve the efficiency of regulated procurement in the electric power industry

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Abstract

This article considers ways to improve the efficiency of the regulated procurement market by implementing recommender systems into the existing procurement IT infrastructure. Using state, municipal and commercial procurement of electric power products as an example, the article considers promising classes of recommender systems for implementation, proposes a methodology for developing such services, and discloses algorithms for processing, configuring and interpreting data necessary for their operation. The difference between the author's approach to creating services and previously published works is substantiated, testing and A/B testing are carried out, and an assessment of the effectiveness is presented. The results obtained have scientific novelty (the methodology of using neural networks in relation to the procurement industry has been substantiated) and practical significance (the customer's time saved on searching for suppliers by up to 40%; the pool of potential suppliers has been expanded; supplier risks have been diversified by selecting relevant procedures from new areas and from new customers; suppliers have been provided with the opportunity to find up to 2–3 new customers for 1 recommendation mailing with a frequency of 1–2 times a week). We proposed to implement the developments in the practice of the operator of public procurement tenders. The authors see further development of recommendation services and solutions for the procurement industry in improving the analysis of semantic (text, logical) content of procurement documents, as well as the behavioral strategies of suppliers. The risks and limitations are associated with the high cost of maintaining a staff of developers-practitioners in neural networks, possible hallucinations of neural networks and their high sensitivity to errors and original data sets.

Keywords: recommender systems, efficiency of regulated procurement, probability of winning in public procurement, personalized recommendations, "non-closing" of tenders, competition in procurement

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Introduction

Improving IT solutions and developing a digital ecosystem for public procurement, procurement of companies with state participation (hereinafter referred to as public procurement, regulated procurement) are priority tasks reflected in the state program of the Russian Federation "Public Finance Management and Regulation of Financial Markets" for the period up to 2030 [1]. In the early stages of the program's implementation, digitalization of procurement solved a particular number of problems: organizing electronic interaction between customers and suppliers; accelerating procurement procedures; reducing barriers for entrepreneurs to enter the public procurement market; increasing competition and the transparency degree of tenders; and minimizing the corruption elements. In the past few years, the development of information technologies in this field has faced new challenges which are reflected in the priorities for the development of the industry in the period from 2025 to 2030. According to the authors of the study, this is due to the trends emerging in e-commerce in general. Thus, at present, the following performance indicators like system speed, fault tolerance, storing and processing significant volumes of data, and the confidentiality guarantee are no longer competitive advantages of information systems: this is a mandatory set that guarantees survival in the market. The strengths of modern IT solutions lie in built-in algorithms and services that make it possible to predict the consequences of management decisions, while not requiring special programming skills from the user. Hence, the implementation of such developments allows one to reduce the risks and negative consequences of decisions made for the financial and economic activities of the organization. With the use of predicting services, it becomes possible to minimize transaction costs for operational tasks, ensuring the sustainable functioning of the enterprise and the achievement of its objectives. As for the field of regulated procurement, over the past three years the problems of effective "closing" of tenders (successful conduct of the procedure, with determination of the winner and signing a contract with him) have been acute issues, with high risks of contract termination, as well as maintaining an optimal level of competition in procurement. "Failure to close" procurement procedures, suppliers' absence at tenders are often associated with unfavorable price and terms and conditions of contracts established by government bodies (buyers) [2]. The risks of current contract termination might be caused not only by force majeure on the supplier's side, as is often believed, but also by entrepreneurs' overestimation of their production capabilities and resource constraints. This problem can be considered following the example of state and municipal procurement, where the statistics are most accurate. According to a report from the Ministry of Finance of Russia, 323 131 contracts were terminated in 2023 for a total of RUB 708.5 billion, which is 9.2% of the total number and 5.9% of the total value of contracts signed in 2023. Similarly, in 2022, the number of terminated contracts constituted 295 072 units, which amounted to 9.2%of the total number and 5.9% of the total value of contracts [3]. According to the report for the 1st and 2nd quarters of 2024, the termination statistics slightly improved in terms of the number of contracts (fewer) and worsened in terms of value (the total value of terminated contracts increased [4]). Thus, there have been no significant improvements in the termination statistics yet. As for competition in tenders, this indicator in regulated procurement formally answers questions about the presence of a sufficient number of participants in commodity and industry markets, as well as the presence of biases towards purchases from a single supplier (contractor, performer), cartels and other anti-competitive agreements. For a more accurate illustration of this phenomenon, we could see the statistics of government procurement since 2022. The level of competition also fluctuates within 2–3 applications per one tender against 4.2 in the period before the pandemic caused by the COVID-19 coronavirus [5]. The Ministry of Finance notes an increase in the number of purchases from a single supplier and sounds the alarm about negative trends in terms of competition.

Analyzing all of the above, it is quite difficult to determine which problem has a higher priority. There are two aspects which need to be considered in cases of "non-closure" of tenders. The first one is low competition due to the passivity of suppliers, their ignorance of the conditions and opportunities of the market, fears of failing to cope. Another one is high demands of customers, leading to the signing of contracts with very weak players, a single supplier, or, to the refusal of suppliers to enter the regulated procurement market in general. In such a situation, it seems that there is an imbalance between the goals pursued by government bodies and suppliers in the government procurement market and the information they have. This is confirmed by a large-scale study by the team from HSE University which highlights "a discrepancy between the criteria for the efficiency of procurement which government and suppliers are guided by in their current activities and the goals that the procurement regulation system is currently focused on" [6]. Government and state-financed organizations strive to demonstrate high competition in their purchases with an enhanced cost efficiency, a minimum number of contract terminations, while suppliers are focused on minimal competition and keeping the price reasonable. However, both parties agree on the contract termination policy: they aim to fulfill their contracts without negative consequences. According to the author, the importance of regulated procurement for the country's economy determines the need to maintain a balance of actors' interests in this market by increasing their awareness. It comprises clear understanding about the nature and state of the market, prospects and feasibility of conducting procurement procedures or participating in them at any given time, in a particular region and under other specific conditions relevant to the current level of technological development. We claim that whole market awareness can be raised through active digitalization and introduction of *recommendatory predictive systems* that will stimulate suppliers to participate in tenders. The recommendatory predictive systems allow one to select procurement procedures relevant to the scale, experience and resource availability of companies for successful participation in them. For the government, the development of such services in procurements brings many advantages: their procedures are applied for by those suppliers who have the potential to fulfill contracts at a real level of competition among worthy market players, and, therefore, the risks of unfair performance or termination are significantly reduced.

Thus, the purpose of this study is to justify the use of a specific class of recommender systems to improve the efficiency of entrepreneurs' participation in regulated procurement and to demonstrate the operation of the service using a separate industry/sphere as an example. To show the novelty of this approach, the following theoretical aspects of the issue should be considered.

1. Methodology for the development and implementation of recommendation services for the regulated procurement sector

A recommender system (RecSys) is an algorithm that selects and offers relevant content to the user based on available information about the content, the user, his behavior and the behavior of other users, as well as about their utilization of the content [7].

Recommender systems are playing an increasingly important role in today's information and business world. With the ever-growing volume of data and content available to users, it is becoming increasingly difficult to navigate and find the most relevant information. Recommender systems can solve these problems: by analyzing user preferences and context, they can provide personalized recommendations that match the interests and needs of users.

The basic principles of decision support systems (preference modeling, decision making under uncertainty) [8–10] have found partial application in modern recommender system algorithms, but some important reasons (for example, psychological and cognitive aspects) are usually left out. It is worth emphasizing that decision support systems and recommender systems are created to fulfill different goals. A recommender system is focused on predicting what content might be interesting to a user based on his past behavior, preferences and actions of other users, thus achieving personalization of offers through the use of various data processing algorithms and the identification of hidden patterns, often without highlighting any specific choice. A classic decision support system, in turn, is created to help the user make an informed decision under uncertainty, providing an explanation for why one or another alternative is better than others.

In recent years, there has been an explosive growth in the interest of developers and users in recommendation systems in various fields, including e-commerce, social networks, music, movies, news and much more. This can be partly linked to how the theory of choice has changed: for many years, economists talked about "rational choice," when consumer behavior was measurable. Budget constraints often served as measures of the effectiveness of decisions made. The development of the "irrational theory of choice" and the work of Thaler [11], and, in general, interest in behavioral economics, led to the popularization of emotional, social and personal components in decision-making, shopping, sales, etc. It became obvious: it is thanks to recommendations that users receive personalized content that matches their individual interests, all of which significantly increases the usability of most IT services.

As for such a specific area as regulated procurement, the recommendation generation system should work as follows: suppliers are regularly offered a list of the most relevant tenders for them, in which they are expected to participate. In this case, the recommendation can be received through various communication channels: notifications in the user's personal account, email newsletters, notifications via messengers, etc.

In the information field, there are several attempts known to develop and implement recommender systems in the procurement sphere both in the Russian and foreign markets [12–14]. However, they have a number of limitations.

The main approaches on the development of recommendation services in procurement can be divided into five groups [15–17]:

1. Content-based filtering: the algorithm analyzes the characteristics of elements that the user has already "worked with" and offers him similar ones. In the context of a procurement system, this may mean, for example, that the supplier will be offered those tenders in which the customer is located in one of the regions where the supplier has already worked.

2. Collaborative filtering: the algorithm analyzes the history of user activities and searches for groups with similar preferences among them in order to offer new users exactly what others liked: this system is based on the history of user interactions with elements. In the context of a procurement system, this may mean that pools of similar suppliers will be formed, for example, according to the principles of work in one region and within one sphere. Then, if supplier A takes part in a tender, supplier B from the same pool can be recommended to take part in the same tender.

3. Popularity-based recommendations: the algorithm recommends the elements that are most popular among users. This approach can be made more complex by dividing users into clusters and determining the most popular elements based on them. It is most appropriate to use this technology in the case where there is a lack of data on a specific user. In the context of a procurement system, we can recommend, for example, procedures that relate to the most popular areas according to the Russian classification of products by type of economic activity.

4. Recommendations based on subject area knowledge (knowledge-based): the algorithm offers the user elements that are related to those he has already shown interest in. Since the authors rely primarily on the needs of the supplier in this study, this approach is hardly applicable. However, for the customer, its implementation could look as follows: customer A purchased laser printers, and after that the system suggests that he purchase A4 paper, proposing a list of suitable suppliers for this.

5. Hybrid systems (hybrid systems) offer a combination of approaches listed (mainly content and collaborative filtering) to provide the most personalized recommendations.

The authors see the goals of the recommender system in the procurement sphere primarily in raising the number of procurement participants, increasing their activity in tenders and, due to this, improving competition and reducing the number of failed purchases. We have already devoted a number of our works to the problem of failed procedures in tenders [18, 19] and consider it one of the key issues in the efficiency of procurement activities. In this regard, it is inappropriate to use the approach based on popularity (3) since in this way suppliers will be recommended procedures with an already high level of competition. In addition, the procurement process is clearly linked to the time: the opportunity to submit applications and participate in tenders lasts 1–2 weeks on average. Recommendations should also be generated with appropriate frequency. For the generation of recommendations by this approach, tenders which are already accomplished or going to be accomplished soon are considered as making the participation of new suppliers impossible or meaningless since such tenders already become irrelevant. Thus, it can be concluded that in this case the most suitable method for forming a recommender system in the procurement sphere is *content filtering*. Based on this thesis, we will justify the novelty of the approach: until now, recommender systems have not been used on a large scale in the sphere of public procurement, remaining exclusively the prerogative of e-commerce and B2B services.

2. Principles of selecting initial data for forming recommendations

The explosive growth of interest in recommender services is due to the fact that almost all public procurement procedures are now conducted electronically. Electronic trading platforms (ETP) ensure the conduct of electronic trades. To develop their thesis, the authors selected "federal trading operators" from among all the platforms, "federal trading operators" are selected that have the right to conduct purchases of government customers under 44-FZ: Sberbank AST, RTS-Tender, National Electronic Platform (Fabrikant), ETP GPB (Gazprombank), AGZ RT, JSC "EETP" (Roseltorg), Russian Auction House (ETP RAD), TEK-Torg [20]. Another platform can be added to this group – ETP AST GOZ, where state defense order trades are conducted.

The information base of the study consists of data on the activity of suppliers on the platform of JSC EETP (Roseltorg) since 2020 (historical sample) considering open data posted in EIS[2]. The model was trained using participation data from 2020 divided into two-week intervals (in accordance with the average duration of collecting applications for tenders). Testing was conducted for the period October–December 2023. Only electronic purchases in the energy sector published in EIS were considered. That meant that at least one code assigned to the procedure was included in the OKPD2 27 group "Electrical equipment". The choice of goods for the electric power industry was due to their high importance for the life support of customers. It was necessary to preliminarily compile "profiles" of suppliers based on their preferences according to historical data. The following aspects were of interest: supplier characteristics, including what areas of activity they were engaged in (according to the OKPD2 classifier), where (in what regions and on what sites), on what regulatory framework (in accordance with what federal laws tenders were held) and with whom the supplier interacted.

Several types of organizations could act as customers:

- authorities, budgetary network institutions that spend budget funds in accordance with Federal Law No. 44-FZ of 05.04.2013 "On the contract system in the sphere of procurement of goods, works, services to meet state and municipal needs";

[2] Unified information system in the sphere of procurement, https://zakupki.gov.ru/epz/main/public/home.html

- companies with state and municipal participation (such as PJSC Gazprom, PJSC Sberbank, PJSC VTB, etc.), as well as state and municipal unitary enterprises operating on the basis of Federal Law No. 223-FZ of 18.07.2011 "On Procurement of Certain Types of Legal Entities";
- commercial customers, the conduct of purchases of which is determined only by the Civil Code of the Russian Federation and the rules established by customers.

If the need to collect and process formal characteristics for the supplier's profile (region, main field of activity, etc.) was obvious in the context of making recommendations, then the issue of evaluating interaction in customer–supplier pairs has not been sufficiently studied. This is due to the fact that information about companies' participation in tenders from 2022 is not intended for publication in open sources, which significantly complicates the identification of preferences and behaviors in customer–supplier pairs. Meanwhile, based on their expert experience in the procurement industry, the authors of the study suggested that non-economic relations between customers and suppliers (friendly, kinship, national, religious, political, and others) supplier preferences may also be affected.

First of all, it is necessary to illustrate that the connection between customers and suppliers really takes place: *Table 1* presents an estimate of their interaction frequency for 2022 and 2023. Even leaving out narrower areas of activity (more detailed OKPD2 codes), the share of stable interactions is significant, especially against the background of a reduction in the number of customers (according to data from open sources (EIS in the field of procurement) using the Roseltorg platform as an example), in 2023, compared to 2020, their number decreased by 35%).

The algorithm for generating recommendations consists of the following steps.

1. Formation of a profile of each supplier[3] based on a statistical assessment of their preferences.

2. Collecting information on all relevant published procedures over the past two weeks.

Table 1.

Evaluation of interaction between suppliers and customers within the OKPD2 group 27

Indicator	2022	2023
The share of customer–supplier pairs identified earlier (starting from 2020) on the Roseltorg platform, among all pairs formed during the year, %	19.9	21.1
The ratio of the number of customer–supplier pairs identified previously (starting from 2020) using the Roseltorg platform as an example, to the number of unique customers who showed activity during the corresponding year, %	0.89	0.96
Average level of competition at auctions (average number of applications per tender), %	2.05	2.01

[3] In the context of the task at hand, only those suppliers who have participated at least once in the procedures for purchasing goods according to OKPD2 27 are analyzed here.

3. Preliminary filtering of procedures by price categories.

Today, the practice of segmenting purchases depending on the initial (maximum) contract price [3] has become established in the work of large federal tender operators. Moreover, depending on the segment, different pricing segments are determined, which cannot but affect participation. Usually, 12 segments are distinguished: "up to 100 thousand rubles," "from 100 to 500 thousand rubles", etc. up to the segment "from 100 million rubles," as well as a separate case when the price is not determined. It has been empirically established that the supplier is not recommended for tenders which price does not fall into their price category or the nearest neighboring ones.

4. Calculation of feature values using formula (1):

$$x_i = \frac{\overline{x}_i \cdot n}{N}, \tag{1}$$

where $\overline{x}_i$ – the average share of a given feature in the supplier's history;

n – the number of unique matches of a feature with the supplier's history;

N– the total number of unique values of a feature in the procedure.

5. Calculation of the weighted sum of all the features of the tenders. The weight determines the importance of each feature in the final assessment, and their determination is a separate task that directly affects the quality of the prediction.

6. Ranking of procedures by weighted sums of feature values. The higher the value, the more suitable this procedure is for a specific supplier. Ten procedures with the maximum value are recommended to the supplier.

The algorithm was implemented in Python, mainly using the *numpy* libraries, and partly *sklearn*, *catboos*t, *pytorch*.

3. Development and testing of a prototype of a recommender system

Here is a final list of features on the basis of which the recommendation for a specific supplier will be ranked:

- the presence of a condition that the purchase is intended for small and medium-sized businesses;
- customer;
- the fact of at least one win of the supplier with a given customer;
- customer region;
- the fact of at least one win of the supplier in the customer's region;
- regulatory framework (44-FZ, 223-FZ, commercial procurement);
- the fact of at least one win of the supplier within the framework of the relevant regulatory framework;
- sphere of activity (according to the full OKPD code);
- the fact of at least one win within the relevant field of activity (according to the full OKPD code);
- combining together the sphere of activity and the region of the customer (interpreted as the participation of the supplier in the relevant region in a tender in a specific sphere and, similarly, the fact of at least one win);
- combining together the sphere of activity and the customer (interpreted as the supplier's participation in the tender from the corresponding customer in a specific sphere and, similarly, the fact of at least one win);
- combining together the sphere of activity and the region of the customer (interpreted as the participation of the supplier in the relevant region in a tender in a specific sphere and, similarly, the fact of at least one win);
- combining together the area of activity and the site

on which the notice is published (interpreted as the supplier's participation in a tender on the relevant site in a specific area and, similarly, the fact of at least one win).

The main quality metric of the content filtering model in this case is *recall at K* (*r@K*), that is, sensitivity (completeness) on *K* elements [9]. We will consider such an outcome as a "positive forecast" when the supplier has participated in the recommended tender out of 10 recommended ones (*r*@10). Using sensitivity as the target metric, we strive to increase the number of real recommendations to different suppliers. In this case, these 10 procedures are determined by ranking by the highest probability of participation for a specific supplier. From the point of view of business logic, the most important tender on this list is the very first one as it is the one that the user wants to look through in most cases.

Determining the weights of features plays a key role in calculating the rating. The training data contains information about the participation of suppliers in potentially interesting (pre-filtered) procedures: "1" – participated, "0" – the opposite case. The task of the ranking algorithm is to rate the tenders for a specific supplier so that the probability of participation is maximum among the first ten. In other words, it evaluates which tenders out of the first ten recommended the supplier at least participated in, and then *r*@10 is calculated. Two approaches were used to calculate the rating:

- modeling the probability of participation of a specific supplier in a specific procedure and ranking according to the probability estimates obtained;
- ranking by a weighted sum of values, and the methods for determining the weights may be different.

In the basic version, when building a decision tree model using *sklearn*, the *r*@10 value is 0.21[4].

The following experiments were conducted using the basic model:

1) calculation of the weighted sum (the method for obtaining weights is the sequential exclusion of each feature to identify the most significant ones and setting weights in accordance with the subsequent change in the key metric (*r*@10 = 0.23));

2) similar to the first point the initial values of the features were pre-normalized (r@10 = 0.25);

3) weighted sum calculation (weighting method – Bayesian optimization, target metric – probability of participation in the first ten tenders (*r*@10 = 0.22)).

There was no significant change in the metric; the best option was the second one. Then experiments were conducted with different classification models to improve the metric:

1) random forest (sklearn [21]), *r*@10 = 0.306;

2) gradient boosting on decision trees (catboost [22]), *r*@10 = 0.331;

3) fully connected neural network with one hidden layer, built on *PyTorch* [23], *r*@10 = 0.355.

Random Forest algorithm is an ensemble method based on many decision trees. Each tree is built on a random subsample of the training data (with repetitions), and a random set of features at each node is used for splitting. Gradient Boosting Decision Trees (GBDT) is a modification of the algorithm in which trees are built one after another, each new tree correcting the errors of the previous one [24].

Figure 1 shows an illustration of a neural network built in accordance with point (3). For clarity, the number of inputs was taken to be three. The hidden layer was designed to highlight the most significant features. As the means of activation, ReLU (Rectified Linear Unit) was used. The number of neurons in the hidden layer can be random; in this case their number

[4] Here and below, similar estimates were obtained on a training sample with cross-validation $k = 5$.

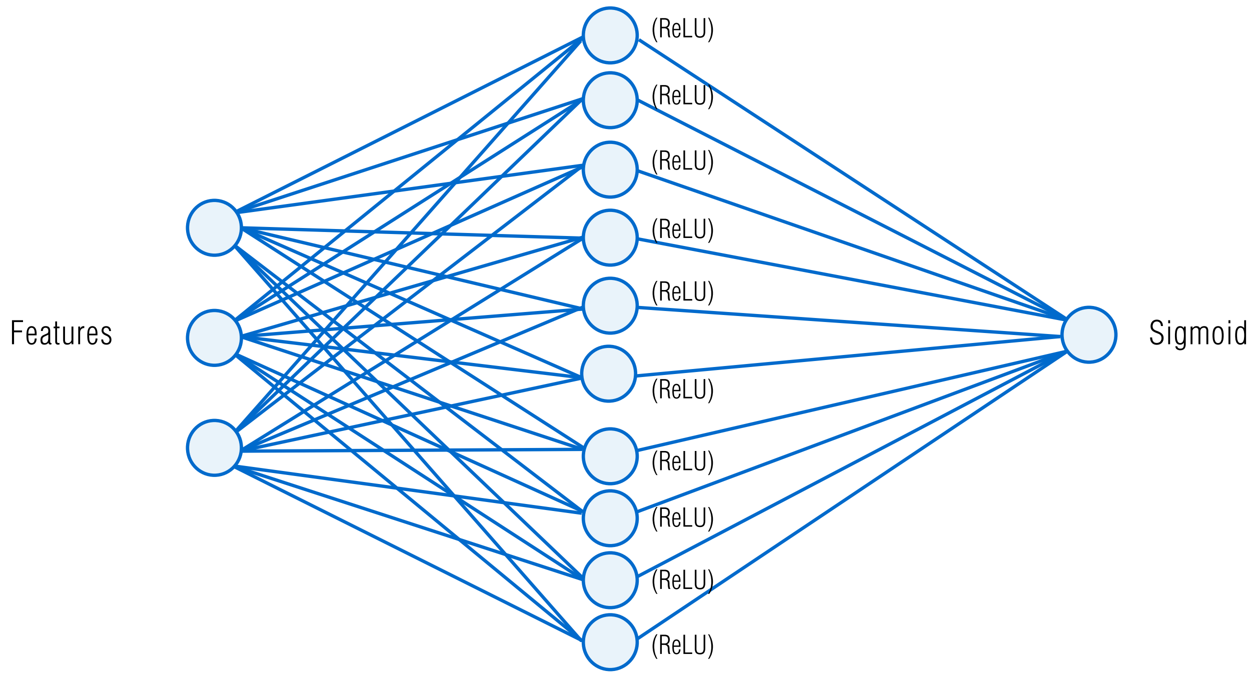

Fig. 1. Architecture of a fully connected neural network for predicting supplier participation.

based on the results of the experiments was taken to be 10. The activation function of the output layer is sigmoid (logistic function) and returns a number in the range from 0 to 1.

The neural network was trained using the Focal Loss function. This is a modification of the cross-entropy function usually used in problems with highly unbalanced classes which reduces the weight for easily classified ones [25]. For each batch (data batch), this function was calculated using formula (2):

$$\text{FocalLoss} = -\frac{1}{N}\sum_{i=1}^{N}\alpha_{t_i}\left(1-p_{t_i}\right)^{\gamma}\log\left(p_{t_i}\right), \tag{2}$$

where N is the number of examples in the batch;

α_t is the weighting coefficient for the correct class;

p_t is the predicted probability of the correct class;

γ is the focusing parameter.

The relatively low values of the metric can be explained by the specific field of activity: since the click-rate is of primary interest for the research, it can be estimated that the average supplier interacts with the "content" approximately two times a year. To compare it with the Netflix service in the USA: it is known that in 2019, its catalog contained [26] 47 000 episodes of TV series, 4 000 films and the number of subscribers in the second quarter was 60.1 million people [27]. In 2024, about 7 000 films and TV shows were available [28] (the exact number of episodes of the series was not disclosed, but more than 10 000 new episodes were added in 2024 [29]) to 90 million subscribers (USA and Canada) [30]. At the same time, it is unknown how many "requests" a user makes on average per year, but it can be assumed that at least one (in reality the number must be much higher). Even with such a rough estimate, the average number of interactions with content here is 118 times a year.

It should be emphasized that the behavior of users in the procurement market has its own specifics, which differs quite significantly from the standard areas of recommender systems application. The distribution of activity among suppliers is uneven – within some OKPD2 categories, the number of participations per year can exceed 1 000. At the same time, any actions of the supplier on the tender page (views, downloads, etc.) can be considered as a fact of "activity."

As confirmed in experiments, the larger the pool of purchases potentially suitable for a supplier, the more difficult it is for relevant tenders to get into the top 10. On average, a supplier can actually be suitable for quite a few procedures, so the complexity of ranking increases. The decisive factor is the interaction between suppliers and customers.

Nevertheless, the benefits of implementing a recommendation system in the work of the platform were substantiated as part of A/B testing. For this purpose, two similar in number groups of suppliers working on the trading platform according to OKPD2 27 were identified. Testing was carried out at 10 weekly intervals at the end of 2023. Each member of the groups received an e-mail containing the top ten recommended tenders. For each e-mail, the number of openings and transitions from the e-mail to the platform was counted. At intervals 6–9, recommendations were sent out according to the described methodology. The rest of the time, the mailing was also carried out, but the recommendations were formed in a "naïve" way: the supplier was offered 10 random purchases that were announced in his region, with activity profiles in which he already worked and the price category of which suited him.

It was necessary for the composition of these groups to be homogeneous. That is why they were selected so that each had approximately the same proportion of active and inactive clients and approximately the same proportion of preferred price categories of purchases. It was also necessary that the average frequency of opening e-mails with "naïve" recommendations sent before the experiment was not supposed to be significantly different (in fact, the difference was no more than 2%), and the groups themselves were practically identical in number.

Group A suppliers were emailed every two weeks with a list of 10 tenders recommended for each to participate.

The results are presented in *Figs. 2* and *3*.

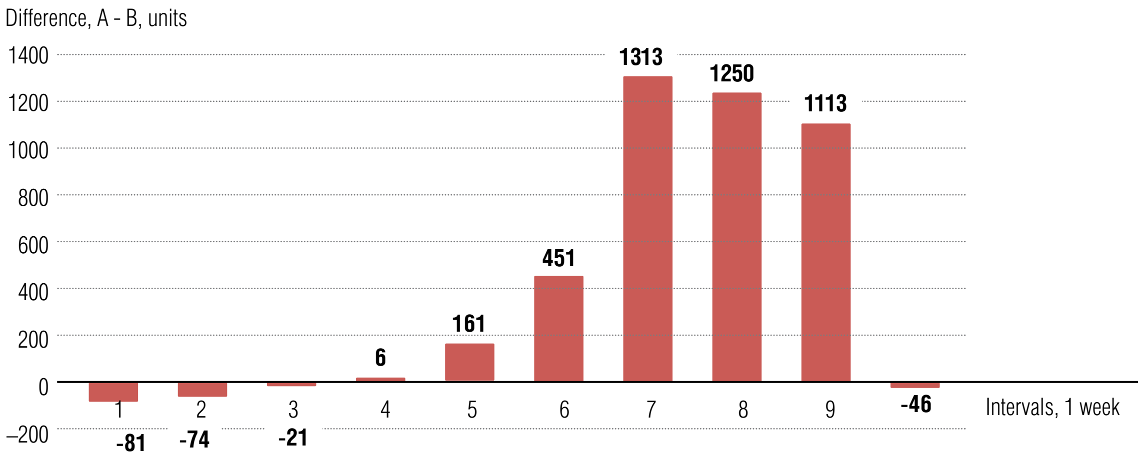

Fig. 2. Difference between the number of views of the letter with recommendations for group A and the same indicator for group B.

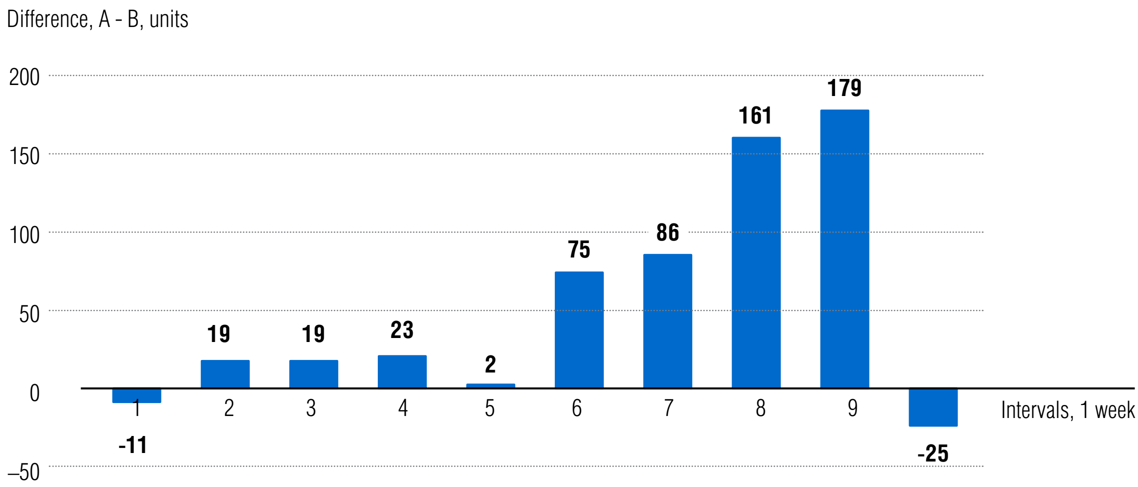

Fig. 3. Difference between the number of clicks to the site from a letter with recommendations for group A and the same indicator for group B.

Thus, it can be concluded that the recommendation emails were perceived positively and with interest by clients, stimulating them to additional actions, and contributing to their information. Due to this, positive effects were obtained for the competitive environment in the tenders (auctions).

4. Results and discussion

The proposed developments have already been partially implemented in the work of the trading operator JSC EETP (Roseltorg), which ensured an increase in the number of successfully completed procedures by 3.7% [31]. In general, customers improved the effectiveness of supplier searches by 40%. Of course, this also works in the opposite direction: if customers find suppliers for contracts and agreements more often, then entrepreneurs are more likely to open new relevant sales markets for themselves and are less likely to encounter problems with contract termination. However, despite the positive experience and optimistic prospects, the authors also note the risks of implementing recommendation services. Firstly, with the rise in the number of parameters on the basis of which recommendations are built, there is a risk of increasing the "noise level" of the model. Secondly, developers can spend significant time and computing power on collecting, processing and storing secondary characteristics without identifying a priority group of parameters due to which the most accurate recommendation is formed. To avoid such risks, industry experts should be involved to adjust the substantive part of the development. Another group of risks is associated with overtraining of the system, which can occur due to an imbalance in the initial data (for example, due to the popularity of a number of categories of the OKPD2 classifier), excessive complexity of the model (then the algorithm will "memorize" individual preferences of the most active clients instead of identifying common features).

It is also impossible to underestimate the risks of the "human factor" – errors during A/B testing, which is aggravated by the high sensitivity of a system to error; the high cost and complexity of technical support and staffing of such developments.

Conclusion

Thus, as a result of the research carried out, the authors' team completed the following tasks:

- formed a hypothesis on the feasibility of using recommender systems to improve the efficiency of state, municipal and corporate procurement (regulated procurement);
- studied the typologies of systems and substantiated the choice of a specific class of systems that is most relevant for developing recommendations for participants in the regulated procurement market;
- developed a prototype of a recommender system, for which he substantiated the methodology for its construction and the data structure for its content;
- tested the prototype on procurement for the electric power industry by sending out recommendations to participate in specific tenders to entrepreneurs who could potentially, due to their market position, both win the procedure and effectively fulfill the contract.

The research carried out allowed us, firstly, to expand the problems of assessing and improving the efficiency of regulated procurement. Currently, efficiency in this area is determined by the level of competition (the number of applications per 1 procedure) and the resulting savings (how much cheaper than the initial declared price it was possible to purchase). However, qualitative indicators such as personal preferences of procurement participants, factors for choosing certain procedures or customers remained poorly studied. Personalized recommendations allow for a better study of market participants' moods and capabilities, and make it possible to improve the efficiency of trades.

Secondly, the results of the study were significant for science and practice. In particular, a methodology was developed for building recommendation services for government needs, rather than for solving purely commercial problems. In the future, such a methodology can be replicated in other areas where the government is a counterparty. As for practice, it is planned to transform the prototype into a full-fledged system and subsequently fully integrate it into the work of the trade operator.

Further research areas, according to the authors, may be more applied in nature, focused on customizing recommendation services for the specific industries, as well as studying the capabilities of other classes of recommendation systems. ■

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