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INTELLECTUAL ANALYSIS OF SCIENTOMETRIC INDICATORS OF RUSSIAN COMPUTER SCIENCE JOURNALS

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Abstract
The article discusses issues related to forecasting scientometric indicators and clustering Russian scientific journals in the field of computer science with the aim of evaluating the current state of science and the progress of research in the country, as well as the state of the competitive market for scientific publications. The study is based on the intelligent analysis of results using forecasting models such as ARIMA, ETS, and nnetar, developed in the RStudio environment. The research findings can be valuable for representatives of scientific journal publishers in the field of the State Classifier of Scientific and Technical Information (GRNTI) "Informatics. Information Technologies" when forming development and promotion strategies in a dynamically changing scientific world. The forecasted results indicate that most industry representatives will maintain their current indicators or change insignificantly, but there is potential for the emergence of new journals. It has also been revealed that journals not included in the Higher Attestation Commission (HAC) list often show slower growth, which is directly related to changes in the calculation of the Science Index indicator since the spring of 2023. However, inclusion is not a guarantee of growth at the moment. Significant growth is observed only in journals that are either classified as category 1 by the HAC or classified as category 2 by the HAC and are included in the Russian Science Citation Index (RSCI) Core simultaneously.
Keywords: scientometric indicators; publication activity; scientific journals; information technology; forecasting; intellectual analysis
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ИНТЕЛЛЕКТУАЛЬНЫЙ АНАЛИЗ НАУКОМЕТРИЧЕСКИХ ПОКАЗАТЕЛЕЙ РОССИЙСКИХ НАУЧНЫХ ЖУРНАЛОВ ПО ИНФОРМАТИКЕ

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Аннотация
В статье рассматриваются вопросы прогнозирования наукометрических показателей и кластеризации российских научных журналов по информатике с целью оценки текущего развития науки и прогресса научных исследований по тематике в стране, а также состояния конкурентного рынка научных изданий. Исследование базируется на интеллектуальном анализе результатов использовании моделей прогнозирования ARIMA, ETS и nnetar, разработанных в среде RStudio. Результаты исследования могут быть полезны для представителей издательств научных журналов рубрики ГРНТИ «Информатика. Информационные технологии» при формировании стратегии развития и продвижения в динамично меняющемся научном мире. Полученные результаты прогноза свидетельствуют о том, что большинство представителей отрасли сохранят свои текущие показатели или изменится незначительно, однако, существует потенциал для вхождения новых журналов.

Также было выяснено, что зачастую меньший рост показывают журналы, не входящие в Ядро РИНЦ, что напрямую связано с изменением расчета показателя Science Index от весны 2023 г., однако, вхождение также не является гарантией роста на текущий момент. Тогда как заметный рост отмечен лишь у журналов, которые или причислены к 1 категории ВАК, или причислены ко 2 категории ВАК и входят в Ядро РИНЦ одновременно.
Ключевые слова: наукометрические показатели; публикационная активность; научные журналы; информационные технологии; прогнозирование; интеллектуальный анализ
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INTRODUCTION

The study and analysis of peer-reviewed scientific journals are essential components of assessing the development of a scientific field within a specific country. Peer-reviewed publications serve as the key source for disseminating information within the scientific community and contribute to the spread of accurate and reliable research findings [18]. They provide a platform for researchers to share their results and ideas while also receiving rigorous evaluation and feedback from colleagues [2]. The peer-review process ensures the quality and reliability of published research and helps maintain the integrity of the scientific community.

In the analysis of the publication activity of scientific journals, various scientometric metrics and indicators are taken into account, measuring the conditional influence, visibility, and influence of journals [20]. The analysis of these indicators provides researchers with a comprehensive understanding of the state of research in a particular field and aids in identifying emerging trends and key knowledge generation centers.

For publishers aiming to promote their journals and gain a competitive advantage in the scientific community, it is also crucial to assess the scientometric indicators of competing journals. Systematic analysis enables publishers to identify the strengths and weaknesses of competing journals in terms of citation, publication frequency, international collaboration, and other significant factors. This, in turn, helps improve existing editorial strategies, identify potential collaboration opportunities, and develop targeted marketing campaigns to attract authors, reviewers, and readers.

Furthermore, the analysis of the effectiveness of journals operating in a specific scientific field within one country allows for comparative analysis and comparison of national and international indicators [21]. Comparing scientometric indicators of journals within a country with those of other countries enables the evaluation of a country's position and contribution to the global research landscape. It also assesses the competitiveness of research institutions and informs resource allocation decisions, fostering increased collaboration and partnership to strengthen scientific production within the country.

For a variety of reasons and the relevance of the field, the conducted research is primarily based on the thematic direction of informatics and information technology. Specifically, it focuses on scientific journals belonging to this subject area. However, the methods used and the model being developed are not tied to any specific direction. The GRNTI category "Informatics. Information Technologies" on the main Russian scientific platform eLIBRARY.RU is represented by 337 journals, which is fewer than 33 other GRNTI categories (excluding multidisciplinary ones) out of 68 (as of May 1, 2023) [16]. Among the journals in the field of Informatics, only 98 scientific journals are currently publishing, accepting publications in Russian, and indexed in the Russian Science Citation Index (RSCI), of which only 55 are included in the list of recommended journals HAC as of May 2023 [4]. In the author's opinion, this is insufficient for such a significant field of science and requires further study.

MATERIALS AND METHODS

Intellectual models can become a preferred approach for data analysis due to their exceptional capabilities in uncovering complex patterns and extracting significant insights from intricate datasets. L. Leydesdorff developed his own model for analyzing time series data as early as 1990, which was applicable to data on national productivity across countries in the European Economic Community (EEC) and the United States [9]. A. Fernández-Cano and M. Torral evaluated the application of various analytical methods for classifying time series data of scientific growth, ranging from visual analysis of deterministic graphs to curve fitting using exponential smoothing and autoregressive integrated moving average models. Tseng Y. H. and co-authors used multiple trend indices to identify emerging research topics [17].

One of the widely used intellectual models that can be employed in scientometric analysis is the ARIMA (AutoRegressive Integrated Moving Average) model [3; 13].

ARIMA, a time series forecasting model, helps predict future journal indicators by analyzing historical data. It examines patterns and trends in metrics like citations, publication frequency, and impact factors, offering insights into a journal's growth [8; 11]. Vasileiadou E. utilized ARIMA modeling to study the dynamics and types of research collaboration [19].

The nnetar model, based on neural networks for autoregression, applies deep learning concepts and algorithms to model complex dependencies between historical series values and their future values [8]. The neural network adapts to the characteristics of the time series and can capture nonlinear relationships and the dynamics of the series.

The ETS model, or exponential smoothing of time series, is a classic statistical forecasting method widely used in time series analysis [11]. This method is based on the idea of smoothing and assigning different weights to historical values of the series to obtain a forecast based on exponentially weighted averages. ETS takes into account trends, seasonality, and random factors in time series, allowing it to model various features of their behavior.

The selection of these three methods—auto.arima, nnetar, and ETS—is driven by their combined advantages and the ability to complement each other. The automatic ARIMA model (auto.arima) offers convenience and ease of use, as it automatically selects the optimal model parameters based on information criteria. The nnetar model, on the other hand, provides flexibility in modeling nonlinear dependencies, which can be important for predicting journal rankings. The ETS model complements the previous two models by accounting for trends and seasonality, enabling a more accurate capture of various characteristics of time series data. The combined use of these three models allows for the consideration of different aspects and characteristics of journal ranking data, enhancing the accuracy and reliability of forecasts, as well as their comparability.

However, it is important to note that the successful application of these methods requires careful consideration of the data, model assumptions, and appropriate validation methods to ensure the reliability and stability of the estimates.

Scientometric indicators can vary depending on the database in which they are calculated [6]. The scientific electronic library eLIBRARY.RU is the largest scientific database in Russia, and its indexing is a primary requirement for the existence of a scientific journal. eLIBRARY.RU accumulates over 56,000 scientific journals, of which more than 5,600 journals are indexed in the RSCI. Users of the platform can analyze the publication activity of each journal, including changes in various indicators over the years. However, the mentioned indicators are mostly interrelated and correlated based on calculation methods. Based on the existing policy for regulating scientific activities, the primary indicator can be considered the journal's ranking in the Science Index. The integral indicator of a journal in the Science Index system takes into account most of the mentioned indicators and indexes, and therefore, despite the theoretical shortcomings of its calculation method, it will be prioritized in assessment and forecasting [12].

The forecasting involves predicting the journal ranking indicator in the Science Index for each individual journal based on time series. The input data include a column with dates and subsequent columns representing ranking indicators for only 30 journals that have consistently published from 2012 to 2021 (Table 1). In this analysis, indicators were forecasted for not all journals but only for established publications that have been consistently published for the last 9-10 years. This limitation is due to the fact that these journals are the main leaders in the market and exhibit stable trends that can already be used for forecasting. Analyzing the indicators of such journals will help understand and forecast future trends and changes in the industry.

Таблица 1

Структура и пример части данных по изменению показателя журналов
в рейтинге Science Index для прогнозирования

Table 1

Structure and example of the data part on the change in the index of journals in the Science Index ranking for prediction

DateJ	J75402	J7310	J27958	J28165	.	J74841
01.01.2012	2,087	2,346	4,045	1,518	.	1,896
01.01.2013	2,397	2,787	4,352	1,942	.	2,342
01.01.2014	2,66	2,743	5,122	2,41		2,427
01.01.2015	2,986	2,964	4,783	2,924		2,604
01.01.2016	2,804	2,956	5,27	2,883		3,036
01.01.2017	2,92	3,183	5,307	3,149		2,901
01.01.2018	3,537	3,454	5,318	3,171		3,245
01.01.2019	4,006	3,557	6,022	3,176		3,251
01.01.2020	4,027	3,882	5,649	3,063		3,713
01.01.2021	3,694	4,239	6,365	3,112		3,441

All three models use the journal's rating history as the primary predictor for forecasting future values, specifically the indicator for the year 2022. They take into account the temporal dependency and changes in the rating over time. The output of each model consists of forecasted rating values for the year 2022 for each individual journal based on historical data.

It is important to note that for the purpose of clustering and analysis, predictors were selected based on their influence on an author's decision when choosing a journal to publish their research results. In other words, they were chosen from the author's perspective and interests. Authors typically choose journals based on factors such as indexing, a limited number of indicators (if there are requirements from their organization or personal preferences), and the perceived "complexity" of publishing in a journal, which is subjectively assessed by each author.

Based on this, and considering the high need for journals to attract new authors, the predictors considered during clustering were chosen to reflect relevant factors that distinguish a journal from the author's perspective. Thus, the clustering of the 59 scientific journals in the sample was based on a combination of several indicators (Table 2):

1. "SI" (journal ranking indicator in the Science Index).
2. "Articles" (the number of articles published by the journal in the last year).
3. "HAC" (the journal's inclusion in the list of journals recommended by the Higher Attestation Commission (HAC), with category information, where the highest category is 3) [19].
4. "CORE" (the journal's inclusion in the Russian Science Citation Index (RSCI) core).
5. "PERIOD" (average number of days for an article to be published after being received by the editorial office).
6. "REJECTION" (the proportion of publications rejected by the journal's editorial board).

These predictors were chosen to provide a comprehensive view of the factors that matter most to authors when selecting a journal for publication and to enable effective clustering and analysis based on these criteria.

Таблица 2

Структура и пример части данных по журналам для кластеризации

Table 2

Structure and example of log data part for clustering

Journal	SI	Articles	HAC	CORE	PERIOD	REJECTION
J10273	3,376	59	2	0	90	0,2
J10570	6,938	38	3	1	180	0,5
J11926	3,94	30	3	0	30	0
…						
J9678	6,42	47	0	1	90	0,05

Attracting new authors is a crucial component of the vitality and success of a scientific journal. This is driven by the desire to draw in promising new authors, as their research and publications can significantly enhance the prestige and reputation of the journal. Evaluating competitors based on their attractiveness to potential authors helps journals understand their position in the scientific publishing market and identify unique advantages they can offer. It also enables the development of strategies for attracting and retaining talented authors, contributing to the growth and prosperity of the journal.

The selected forecasting and clustering models are implemented in the RStudio environment using the R programming language [14-15]. R provides the necessary tools and libraries for data analysis at all stages, from data processing to the visualization of results [10]. When working with models for analyzing scientometric indicators of scientific journals, several libraries were used, including "Tidyverse," "nnet," "forecast," "cluster," "randomForest," and others.

Forecasting the Science Index journal rating includes three similar blocks: ARIMA, nnetar, and ETS.

For example, ARIMA: The data is transformed into time series and analyzed using auto.arima() from the "forecast" package. A model is built for each object, and forecasts are made one step ahead. The results are stored in the variable predicted_values_autoarima.

Forecasts are generated using the print() function. A combined dataframe with the results of all three methods is created using cbind(). Then, a column with the object number is added, and the "model" and "forecast" columns are removed from combined_results_selected. The data is transformed into a long format using pivot_longer() from "tidyr."

Next, a comparison chart of forecasts is created using ggplot(). Data is sourced from combined_results_long, where the "Object" and "Forecast" columns define the X and Y axes. The chart uses the "bar" geometry to display forecasted values by methods.

Additionally, a "boxplot" chart is created to compare the accuracy of forecasting methods. The geom_boxplot() function is used to display the spread of values by methods.

As a result, the model provides users with forecasted Science Index journal rating values for 2022 for each method (ARIMA, nnetar, ETS) for each data object (journal).

The model also performs a cluster analysis of journal data using the random forest method after loading the necessary packages and reading the data. Rows with missing values (NA) are removed using na.omit(), while object identifiers are stored in the variable object_ids.

Then, the column of object identifiers is removed from the data. A min_max_normalize function is created to normalize the data using the min-max method with weights considered.

In the next block, data clustering is performed using the Random Forest algorithm. A Random Forest model (rf_model) is created, and clustering is carried out on normalized data, excluding the last column. Then, a proximity matrix (prox_matrix) is extracted from the Random Forest model, reflecting the similarity between objects.

Next, the optimal number of clusters is determined using the elbow method [1]. For each value of k from 2 to 10, the sum of squared distances within the cluster (WSS) is calculated. Then, the derivative and second derivative of WSS are computed. The optimal k is determined as the first value of k at which the second derivative of WSS becomes negative.

Data clustering is performed using the optimal number of clusters (optimal_k) with the help of the cutree function, and the result is stored in the variable cluster_assignments. The clusters are added to the normalized data as a new column called "Cluster."

Then, a data frame wss_df is created containing WSS values for k from 2 to 10. A wss_plot is generated using ggplot2, showing the relationship between WSS and the number of clusters (k) and highlighting the optimal k with a red dot.

Finally, box-and-whisker plots are created for the values of the silhouette width in each cluster, displaying the distribution of values for each cluster.

As a result of executing this model, the user receives cluster labels, the optimal number of clusters, and corresponding plots.

RESULTS

The comparison of forecasting results indicates the relative similarity among all the methods used. Often, the difference between values is around 0.2-0.3 units, occasionally reaching 1 unit for journals with initially high values in the Science Index journal ranking and a sharp positive change in recent years (see Figures 1-2).

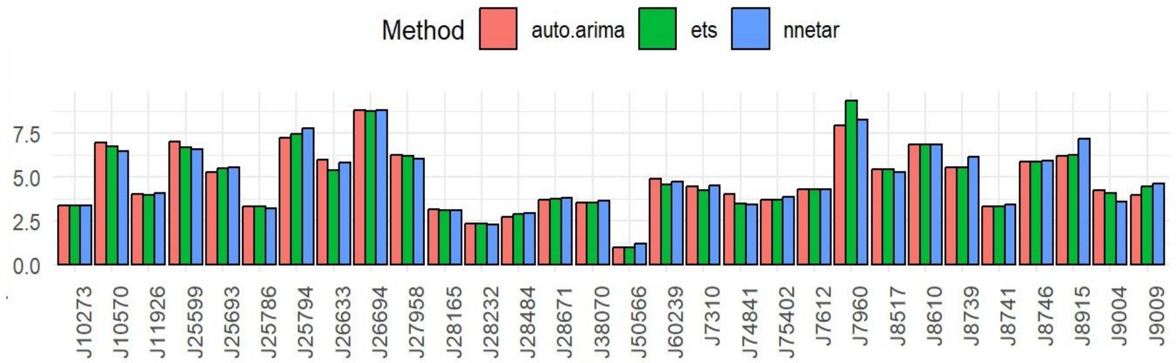


Рис. 1. Сравнение результатов прогнозирования интеллектуальной модели (Прогнозируемое значение/Объект)

Fig. 1. Comparison of intelligent model prediction results (Predicted value/Object)

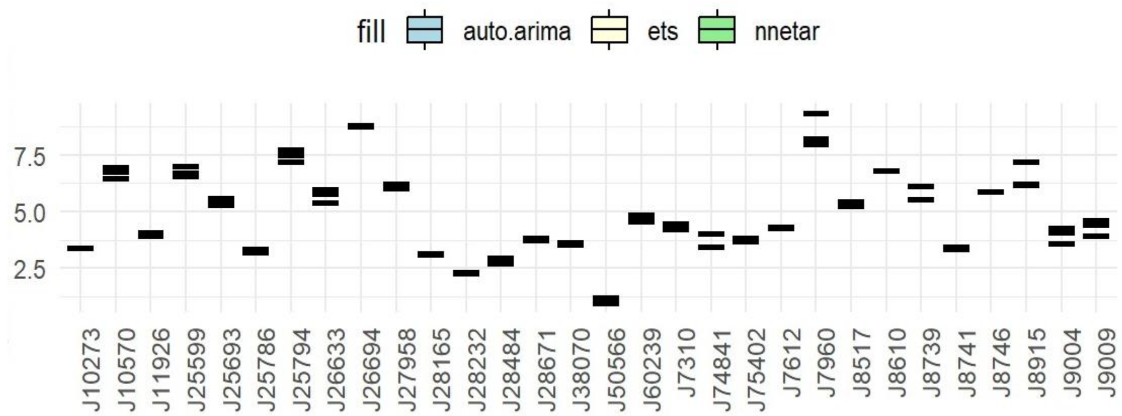


Fig. 2. Comparison of forecast accuracy of the intelligent model (Predicted value/Object)

Рис. 2. Сравнение точности прогнозов интеллектуальной модели (Прогнозируемое значение/Объект)

Furthermore, based on the obtained Mean Squared Error (MSE) values, it can be concluded that the auto.arima model demonstrates the best performance among the forecasting models. Comparing the MSE values, it can be noted that the MSE for auto.arima is 7.55, whereas for the nnetar model, this value is 7.62, and for the ETS model, it is 8.17 [7].

Based on these results, it can be assumed that the auto.arima model provides more accurate forecasts with values closer to the actual data (which are currently unavailable). This may be attributed to the advantages of the automatic ARIMA model selection method, which considers various combinations of model parameters and selects the optimal model most suitable for the time series. However, it is essential to note that without actual data, it is not possible to fully assess the quality of the models and claim that the selected model is optimal or correct.

To determine the optimal number of clusters, the Elbow method (WSS) was used, which is based on the sum of squares of distances within clusters. The goal was to choose a number of clusters after which an increase in the number of clusters no longer significantly reduces the sum of squares of distances.

Based on the obtained values, it can be observed that the reduction in WSS slows down after choosing 4 or 5 clusters (see Figure 3). After this point, the decrease in WSS becomes less substantial. Therefore, in this case, the choice was made for 4 or 5 clusters as the optimal number, considering the data structure and volume. Ultimately, clustering was performed with 4 clusters.

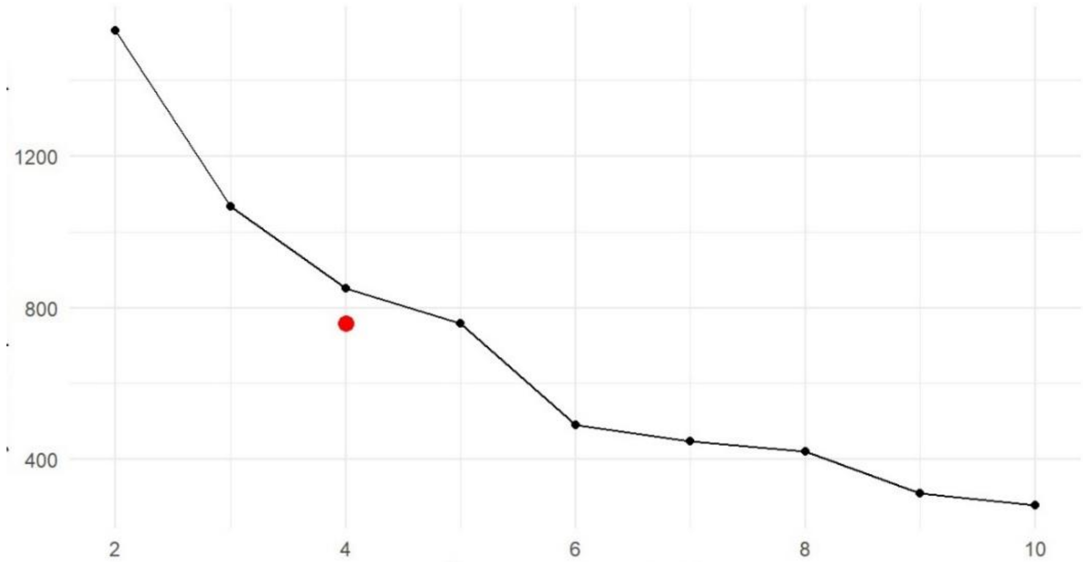


Fig. 3. Variation of the sum of squares of distances within clusters with respect to the number of clusters (Sum of squared distances within the cluster/Number of clusters)
Рис. 3. Изменение суммы квадратов расстояния внутри кластеров относительно числа кластеров (Сумма квадратов расстояний внутри кластера/Количество кластеров)

The evaluation of the quality of the intellectual models for analyzing journal bibliometrics indicates that both the forecasting models and the clustering model are of high quality and can be successfully applied in future practical tasks.

The results obtained from the forecast based on the analysis of a journal's Science Index rating suggest that the majority of journals among the well-established ones in the field, provided they maintain their existing editorial policies, will either maintain their current indicators or experience minor changes. However, six journals have been identified with predicted growth and another six journals with expected significant decreases in their indicators.

It is worth noting that for these six journals with predicted growth, the forecast indicates an increase in their indicators at the level of 0.35, which is less significant compared to existing results but substantial when compared to the industry average. On the other hand, for six journals, a significant decrease in their indicator is forecasted in the range from -0.2 to 1 (see Figure 4). This may be attributed to changes in the journal's research focus, competition with other publications, or issues affecting the quality of publications. Such declines can have a substantial impact on the status and influence of these journals within the scientific community.

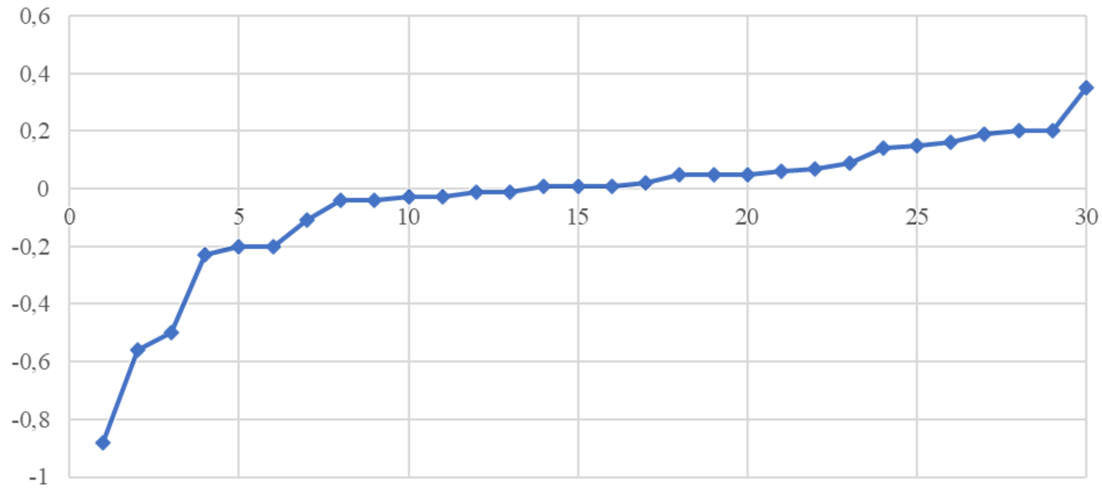
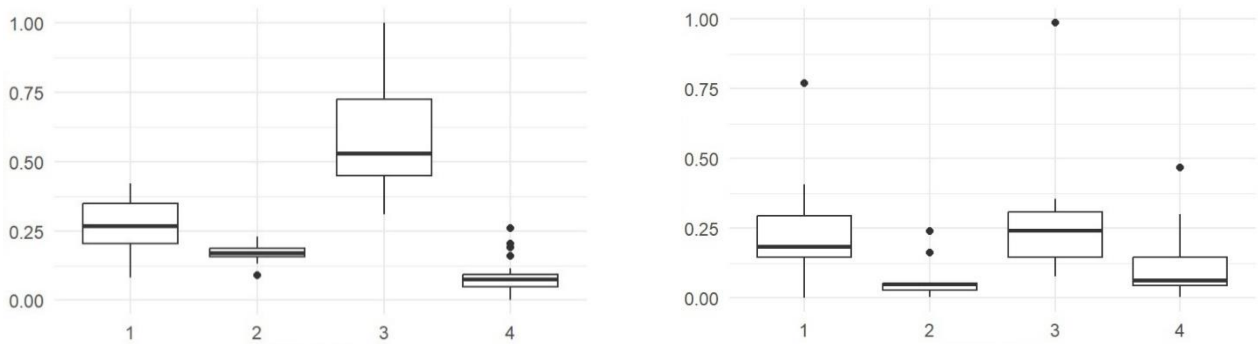


Fig. 4. Projected change in the journal's index in the Science Index ranking for 2022 relative to the current year 2021
Рис. 4. Прогнозируемое изменение показателя журнала в рейтинге Science Index на 2022 г. относительно текущего 2021 г.

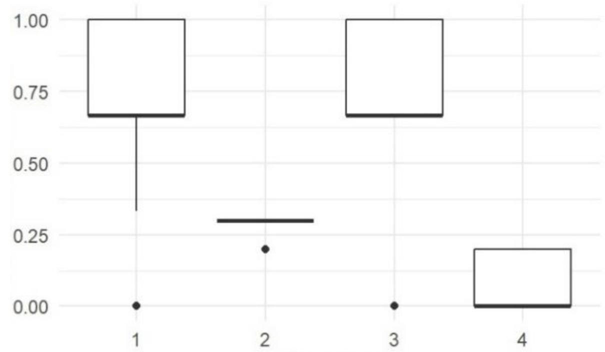
It was also found that journals not included in the RSCI tend to show slower growth. This is directly related to the change in the calculation of the Science Index rating from the spring of 2023. However, inclusion in RSCI is not necessarily a guarantee of growth at the moment. Noticeable growth has been observed primarily in journals that are either classified as Category 1 in the HAC or classified as Category 2 in HAC and are also included in RSCI simultaneously. It can be assumed that such dependencies will become less relevant in the near future due to the recent change in the calculation of the Science Index rating, to which the scientific community has not yet fully adapted.

During clustering, the journals were divided into four groups or clusters, with numbering unrelated to their means. The largest cluster, Cluster 4, included 25 journals with the lowest average Science Index rating within the cluster. These journals rarely even belong to HAC Category 3 and RSCI. Moving down in terms of the number of journals included, Cluster 1 contained 14 journals. It also included journals with unremarkable Science Index ratings, which are more likely to belong to HAC Categories 1-2 but are not part of the RSCI journal list. Both Cluster 4 and Cluster 1 journals share a relatively slow publication pace, but Cluster 1 journals have a higher proportion of rejected articles.

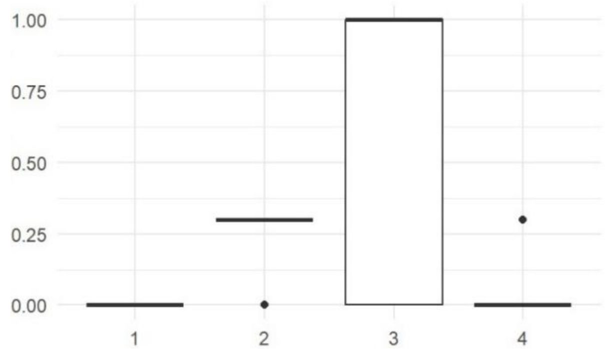
Clusters 2 (9 representatives) and 3 (11 representatives) had more similarities. However, all the journals that combine high Science Index ratings, RSCI inclusion, and HAC Category 1 were placed in Cluster 3, setting it apart from the others. Journals in these categories often reject a larger proportion of submitted articles compared to Categories 1 and 4 and require a significantly longer time for publication, which may be due to a more rigorous peer-review system (see Figure 5).



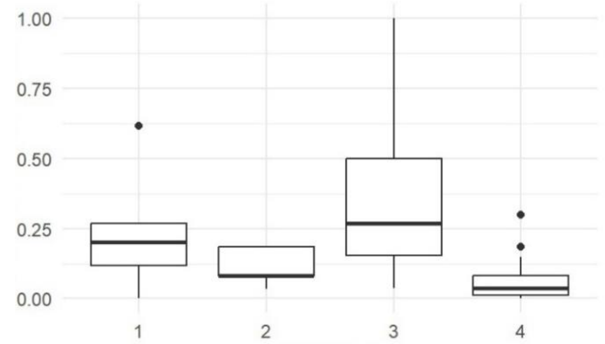
a) Sciecne Index
b) Number of articles



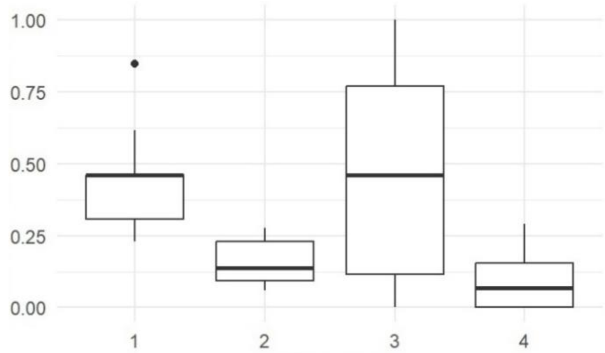
c) Inclusion in the HAC list



d) Inclusion in the RSCI core



e) Publication period (days)



f) Percentage of rejected articles

Fig. 5. Structure of values of journals included in clusters by indicators

Рис. 5. Структура значений журналов, входящих в кластеры, по показателям

In the context of forecasting, it is anticipated that the indicators of journals from Clusters 4 and 2 are likely to decrease, while Cluster 3 may remain relatively stable. On the other hand, Cluster 1 and some Cluster 3 journals are expected to experience growth.

CONCLUSION

The conducted forecasting and clustering of scientometric indicators for Russian journals specializing in the field of informatics have shown relative stability within the industry. This segment of scientific publications is not as numerous compared to some other fields, which affects the assessment but also implies that there is room for new journals in this area. Overall, it is recommended to strive for journal inclusion in the Higher Attestation Commission (HAC) and especially in the Core of the RSCI journal list.

Increase in the number of publications doesn't always lead to improved scientometric indicators, and vice versa. Therefore, it's necessary to find a balance between the quantity of publications and the quality of their content. Maintaining a reasonable time from submission to publication that is convenient for authors is important.

There are journals with high Science Index ratings and a short time to publication, but they also have a significant proportion of rejected works. Achieving such status requires rigorous selection and a commitment to maintaining high publication quality. It's important to strike a balance between a quick review process and rigorous academic selection to attract high-quality and impactful research that contributes to journal metrics.

Author plans to continue working on this research, expanding the scope to consider additional factors and indicators influencing journal development and reflecting its position in the competitive publishing market. This will provide a more comprehensive understanding of the dynamics of scientific journals in the field of informatics and offer valuable insights for journal editors, publishers, and the broader scientific community.

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