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The Special Aspects of Devising a Methodology for Predicting Economic Indicators in the Context of Situational Response to Digital Transformation

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Abstract. The methods currently used for detecting situational deformations in the time series of economic indicators have a number of major flaws, which encourages further research and development in this field aimed at improving the quality and stability of the regression models in the context of digital transformations. The purpose of this research is to devise a methodology for predicting economic indicators in the context of situational response to digital transformation. We examine methods for predicting economic indicators through time series analysis, following which the vector of proactive development can be determined. In order to achieve our objectives, we employed various methods, including mathematical statistics, mathematical modeling, numerical methods, and regression analysis. Our analysis of seasonality in the time series of economic indicators, given the cyclic dominance and modified series, allows us to conclude the need for their structural decomposition with proactive data rejection and modifications and considering their possible displacement. We devised our own original methodology for better processing of statistical data and improved stability of linear regression models ineffective forecasts in the context of situational response of digital transformations. The statistical tools we suggest are likely to enhance the quality of the economic forecasts obtained with the use of regression models (from 15%) due to the preliminary processing of source data and determination of the cyclic dominance of the modified series. The study shows that the methodology for predicting time series in the context of situational response offers the fastest and most accurate data analysis.

Keywords: Cyclic dominance; Linear regression; Model prediction methodology; Situational response; Structural modifications

1. Introduction

Since economic research uses lots of data today, and the results of their analysis are essential, it is really important to get prompt situational responses to digital transformation. If we ignore situational changes that occur in modern economic processes, it can result in a significantly worse quality of the mathematical model and consequently, the real economic situation can be distorted (Egorov *et al.*, 2021). The purpose of this study is to develop a methodology for predicting economic indicators in the context of situational response to digital transformation. The subject of the research is the methods applied for predicting economic indicators with time series and subsequent formation of a vector of proactive development. The scientific novelty of the study is the methodology we propose

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for forecasting economic indicators in the context of situational response based on smoothing situational deformations of time series, their displacement and determining the level of seasonality to digital transformation. It should be noted that even though there is a variety of methods that are used for detecting elements of the situational response of statistical data, for the most part, they are applicable only for one-dimensional samples and, with each iteration of the method, only one deformation of the statistical series is analyzed. This is due to the fact that the slope of the regression line and the seasonality of the series are not considered. The methodological tools described in the scientific literature we have reviewed are sensitive to the volume of the initial sample. Therefore, we need to focus on the important task of developing and implementing an algorithm for adaptation to situational change in the source data and methods of subsequent data processing in order to increase the stability and quality of the paired regression models used in forecasting to digital transformation. Situational changes can be caused by various factors, such as economic crises, political upheavals, technological breakthroughs, social movements, or natural disasters. It is important to be able to analyze and adapt to situational changes in order to function successfully and achieve your goals. Situational response refers to an organization's ability to adapt and make decisions in response to unexpected situations or events. Here's how digital transformation influences situational response: 1. Improved access to data: digital transformation allows organizations to collect, analyze, and interpret vast amounts of data from various sources in real time. 2. Enhanced collaboration and communication: digital transformation enables seamless communication and collaboration across teams and departments, regardless of location. 3. Automation and predictive analytics: through digital transformation, organizations can automate routine tasks or processes, freeing up valuable resources for more critical decision-making tasks. Digital technology has far-reaching effects and can lead to various situational changes, which can be assessed based on the author's methodology.

2. Literary Review

Forecasting is also very different in terms of its content (demography, society, economy, environment, natural resources, etc.) (Nazarychev, Marinin, and Shamin, 2022). Various sources of information can be utilized in forecasts, including accumulated experience that involves understanding the fundamental laws of the phenomena being investigated (Babkin *et al.*, 2021), extrapolation of the existing trend (Egorov *et al.*, 2021), building models of the projected phenomena and objects in the expected conditions (Tanina *et al.*, 2022). Depending on their purpose, forecasts can be normative and exploratory. The former use pre-set goals and define deadlines and ways to achieve them. Exploratory forecasts, on the contrary, follow the trends in the past development of a phenomenon in order to predict its future development (Pishchalkina, Pishchalkin, and Suloeva, 2022). Economic forecasting is helpful in solving several important tasks in the context of situational response (Zhogova *et al.*, 2020). First, there is a need for a scientifically sound and, at the same time, objective picture of future processes based on current indicators. Secondly, the directions of economic activities to choose from must consider forecast estimates. Thirdly, we should identify the present factors that will influence the phenomena we study. For this study, the analysis of today's forecasting methods and models with adaptation to situational changes is very important. In this regard, forecasting that uses time series is essential for economic performance prediction. Quantitatively, this dependence can be measured using a linear coefficient of correlation between the levels of the original series and those of the same series, which are shifted by several steps in time (Hao, 2022). There are many ways and approaches to considering the unavoidable error in the modeling of the time series of economic indicators (Rusanov, Abbazov, and Baluev, 2022; Lemeshko and Lemeshko, 2005). Considering situational change results in building a model, each level of which is a fuzzy number of a triangular type, whose modal value coincides with the relevant discrete value of the clear model, while the carrier of a fuzzy number contains (there is a certain value of the probability function) the value of the corresponding level of a real series (Zainy *et al.*, 2023). Authors cope with the extreme fluctuation of past data due to COVID-19 and other world events in several ways. 1. Acknowledging and addressing the limitations. Authors are aware of the limitations posed by the drastic changes in data and its impact on their research. They acknowledge the uncertainties and potential biases introduced by the fluctuations and make efforts to address them. 2. Offering alternative scenarios or projections. Authors may present alternative scenarios or projections to account for the uncertainties caused by the events (Prasetya, Yopi, and Tampubolon, 2023). 3. Conducting additional research. Authors may conduct additional research to update their data and analysis to include the latest information and reflect the impact of the events under consideration (Grishunin *et al.*, 2022). Thus, the fuzzy model takes into account the error of situational change in economic processes.

3. Methods and Materials

We used the STATISTICA 10.0 software package for calculations. This system can make fairly accurate forecasts in different areas. STATISTICA uses various forecasting methods (Boginsky, 2021). If this difference exceeds a certain threshold, it means there are structural deformations in the data. Situational deformations can be removed from a sample if it contains a sufficient amount of data for analysis and the representativeness of the sample is not reduced. Otherwise, various adjustment methods are used (Egorov *et al.*, 2021). The main ones are manual substitution (used it there are not many structural measurements) (Sandler and Gladyrev, 2020); substitution for the most probable value (Saroji *et al.*, 2022); data interpolation (substitution of structural transformations with the values obtained from similar samples) (Zubkova *et al.*, 2022); proactive smoothing of the data (Zaytsev *et al.*, 2021; Agus *et al.*, 2021). In our study, we employed the STATISTICA 10.0 software package along with several mathematical tools to identify the seasonal component in a dynamic series. This involved seasonal correction using Seasonal Decomposition 1, the X11 Seasonal Decomposition module, and the Multiple Regression module. Additionally, we utilized these tools to assess the stability of linear regression models, which included rejecting certain data points and implementing modifications within the context of situational response. This process encompassed building relevant modifications and forecasts while considering confidence interval bias. The author's methodology for time series forecasting in the context of situational response includes several main stages: Stage 1. Identify and analyze the seasonality of economic indicators. Stage 2. Improving the stability of linear regression models based on data rejection and its modifications in the context of situational response. This method involves randomly selecting subsets of the data multiple times, training the model on each subset, and evaluating its performance. The average performance across all iterations provides an indication of the model's generalization capability.

4. Results

The author's methodology for time series forecasting in the context of situational response includes several main stages.

Stage 1. Identify and analyze the seasonality of economic indicators. The methodology was tested during the analysis of Russia's average per capita monetary income. The evaluations are aimed at proactive forecasting in the context of situational response: 1. The series data of the indicator are visualized: the population's average per capita monetary income for the timely determination of seasonality. 2. The trends of seasonality are determined using the method of Seasonal Decomposition 1 in the context of situational economic development. 3. The seasonality of the economic indicator is identified using the X11/Y2k method (Census 2). As a starting point for further application of Seasonal Decomposition 1 in order to carry out timely seasonal adjustments in the context of situational response, we will analyze the time series of the Russian population's average per capita monetary income, data for the period from the first quarter of 2013 to the second quarter of 2022. According to the results obtained, there are undulating deterministic periods in the fourth quarter, and a minimum value is observed in the first quarter. We move on to the next task, which is aimed at strengthening the study in terms of identifying the seasonality of the economic indicator based on the X11/Y2k method (Census 2). In order to build an effective qualitative model, the source data have to be preliminarily processed so that anomalous measurements can be identified in them. It is shown that regression analysis is an important tool for analyzing experimental data, whose private but effective instrument is linear regression. Given the identified features of cyclic dominance and the formed modified series, we find it reasonable to expand our scientific approach by increasing the stability of the linear regression models based on data rejection and modifications in the context of situational response.

Stage 2. Improving the stability of linear regression models based on data rejection and its modifications in the context of situational response.

The following ones are most commonly applied as the criteria for estimating the adequacy of a paired linear regression model: 1) the coefficient of determination R2 reflects the proportion of variance of the dependent variable explained by regression. In other words, it shows a part of the values of regressor X, which fully explains the behavior of random variable Y with the constructed regression equation. It can take values from 0 to 1. The stronger the dependence between random variables X and Y, the closer the value of the coefficient of determination is to 1, indicating a better fit of the model to the data. Additionally, the F-test is employed to estimate the significance of the regression equation. Based on the data obtained, for a timely situational response, it is proposed to introduce a module of the displacement magnitude of the forecast result, which appears as a result of the original equation correction and changing the type of the new equation after data rejection and its modifications in the context of situational response and further maintaining of proactive development trend of the time series. The author's mathematical model, based on data rejection and its modifications in the context of situational response, will have the following form equation (1):

$$\Delta pr = |(a \cdot Xpr + b) - (ap \cdot Xpr + bp)|, \quad (1)$$

where $(a \cdot Xpr + b)$ is the linear regression equation before situational response;

$(ap \cdot Xpr + bp)$ is the linear regression equation after situational transformations (data rejection and modifications)

Tables 1 – 2 present the results of the method used for increasing the stability of linear regression models due to data rejection and modifications in the context of situational response. The tables contain the values of the coefficients of determination R2 and accuracy T, calculated using a model obtained after rejecting some statistical data in the context of situational response. The quantity of the rejected observations corresponds to the probability of non-occurrence in a given area. Table 3 shows the displacement magnitudes of the estimated forecast value and the values of the confidence interval. The advantages of the first modification of the method where some data is rejected in the context of situational response are: 1) it can be used for multidimensional linear regression models; 2) there is no binding to a specific amount of data, i.e., the value of coefficient k does not change depending on the sample size, while the value of t in this method changes in case the amount of data changes too; 3) simplicity. The proposed method does not require additional calculations or tables.

Table 1 Values of displacement magnitude Δ and confidence interval *(calculated by the authors)*

Probability of entering the area of study given situational response	Method Δ,%	1 modification Δ,%	2 modification, Δ,%	Method CI, %	1 modification CI,%	2 modification CI, %
0				19		
90	5	0.34	7	12.2	15	14.4
85	5.9	0.18	8	11	13.7	14.7
80	6.7	0.134	9	10.5	12.5	14.9
70	7.6	0.14	10.3	10	10.9	15.7
65	8	0.14	10.7	9.7	10	17
60	8.2	0.13	11	9.44	9.4	17.8
50	8.5	0.1	12.6	9.8	8.2	19.4

As can be seen from the table, when using the proposed method aimed at improving the quality of regression models based on changes in the values of situational deformations, the coefficient of determination R2 increases from 0.55 to 0.79. This value is achieved by changing the values of five observations. Thus, it can be concluded that good results can be obtained using the method where situational deformations of time series are searched for and subsequently corrected by applying data displacement and modifications, as well as using the method based on data rejection. Table 2 shows the displacements of the estimated forecast value and the confidence interval values. When applying this second modification to the processing of statistical observations, it is recommended to eliminate no more than 15-20% of the initial values. A larger quantity of eliminated values may suggest that the data exhibit a certain regularity and are not significantly affected by structural deformations.

Table 2 Values of the bias and confidence interval (CI) indicator for linear regression models based on data rejection and its modifications in the context of situational response *(calculated by the authors)*

Probability of entering the area of study given situational response	Method Δ,%	1 modification Δ,%	2 modification Δ,%	Method. CI, %	1 modification CI,%	2 modification CI, %
100				20.82		
95	7	1.69	8.26	15.68	14.34	14.6
85	6	3.1	8.26	8.2	8.86	14.6
80	6	1.95	8.26	8.2	6.4	14.6
77	4.6	1.8	8.5	8.4	6.5	14.7
60	3.36	1.8	8	6.35	6.5	14.4
55	3.7	2.2	7	6.32	5.63	14.4
50	3.21	2.1	6.6	6.37	5.63	14.5

This example (which considers the relationship between the population's per capita monetary income and the average nominal wage, the size of the population (at the beginning of the year), investments in fixed assets, and current prices) shows that the displacement value, given the deformation transformations, is equal to 31306.6. This observation is the next-to-last value of the variation series and has been chosen to visually display the magnitude of displacement in the context of situational response since, at this point, the magnitude of displacement will be significantly greater than at a point equal to the average value of the magnitude. We do not use the last observation of the variation series because it may appear anomalous and far removed from other values of the variation series. As can be seen from the table, positive results are obtained when using the proposed method of detecting and eliminating structural deformations. Once a reliability area is established with a confidence probability of 0.9 for the data within this range, structural measurements can be identified. Applying the method, we can reveal two anomalous observations in this case. Their exclusion from the sample allows us to increase the coefficient of determination from 0.55 to 0.69. Determination coefficient R2 reaches its maximum value with a confidence probability of 0.65 (7 rejected points) and amounts to 0.83. At the same time, if only 4 values are rejected, the value of the coefficient of determination can grow to 0.79, which also indicates the adequacy of the linear regression model in this case. It should be highlighted that these 4 observations are the observations that have been changed in the initial sample for us to run the experiment. If the first modification of the method is used, the maximum value of R2 reaches 0.876 when 7 observations are rejected. However, the abnormal value is not detected because it is quite close to the trend line. Therefore, despite the higher value of the coefficient of determination, in this case, it is preferable to use the method that increase the stability of regression models based on data rejection. The idea of the second method that should improve the accuracy of the regression model is that at the first stage, the same as in the previous method based on data rejection, the boundaries of the area of reliable data are found. Unlike in the first method, the data that do not fall into the area with a given probability are not excluded from the sample but, instead, are moved to the boundaries of this area, resulting in a change in their values. The second modification of the method applied for this experiment allows us to increase the value of R2 to 0.61 by rejecting the two extreme anomalous observations. In all three cases, the value of the bias does not exceed 9%, and the value of the confidence interval goes down compared to the initial one. The first modification demonstrates the minimum displacement value. This is due to the fact that, in this case, one of the structural transformations of independent variable X is not detected. The computational complexity is low, and the average running time of the algorithm is minimal, so the proposed methodology can be used for other indicators. It can be said that positive results are achieved when we apply the forecasting methodology based on using time series in the context of situational response, determining the seasonality of the cyclic dominance of modified series, and using data rejection and modifications with the possibility of their displacement.

5. Discussion

Modern literature describes algorithms for applying various methods to adapt to situational changes (Lemeshko and Lemeshko, 2005). The following ones are among the most common: Grubbs's test, the Titien-Moore-Beckman method, the Acton and Prescott-Lund methods, and Cook's method. We should agree with other scientists that the main advantage of these methods is their simplicity in terms of understanding and application (Kredina *et al.*, 2022). The great strength of these methods is that they can be used to estimate several situational deformations in the sample at once. However, if several values are studied concerning situational response, a value that is not an outlier may fall under suspicion, and other methods will have to be used to check a specific value. Also, the Titien-

Moore-Beckman criterion has the same disadvantage as Grubbs's test. The second degree is used when estimating the criterion statistics, which reduces the accuracy of calculations (Rodionov and Velichenkova, 2020; Prasetya, Yopi, and Tampubolon, 2023). The Titien-Moore-Beckman criterion assumes that the number of k outliers is known in advance, but this is not always the case. The problem in identifying the number of outliers is considered by the Rosner criterion (Tanina *et al.*, 2022). Due to the fact that Cook's method allows you to reject several source data at once, let us compare this method with the modifications of the methodology developed by the author of the present work. Table 3 shows the results of a comparative analysis of the author's methodology for predicting time series in the context of situational response and Cook's method.

Table 3 The results of a comparative analysis of the author's methodology for predicting time series in the context of situational response and Cook's method *(calculated by the authors)*

Method used	Parameters of the method	Numbers of excluded or transformed observations	Quality criterion of the method			
			R2	Δ^2,%	Confidence interval value, %	Number of elementary operations
Cook's method	Dk=0.015	2, 3, 19	0.58	0.9		$\sim 0.4 \cdot 10^6$
	Dk=0.002	2, 3, 11, 19	0.57	0.58		$\sim 7 \cdot 10^6$
	Dk=0.002	2, 3, 11, 14, 19	0.64	0.2		$\sim 7 \cdot 10^6$
Method based on data rejection (1 modification)	k=1.27 (P=0.8) (Dk=0.17)	19, 3, 13	0.7	2.4	15	$\sim 0.5 \cdot 10^3$
	k=1.15(Dk=0.7)	3, 13, 14, 19	0.77	2.03	13.7	$\sim 0.5 \cdot 10^3$
	k=1 (Dk=0.74)	3, 13, 14, 20, 19	0.83	1.5	12	$\sim 0.5 \cdot 10^3$
Method based on data displacement and its modifications (1 modification)	k=1.27 (Dk=0.17)	19, 3, 13	0.53	1.4	18	$\sim 0.5 \cdot 10^3$
	k=.15 (Dk=0.7)	3, 13, 14, 19	0.6	1.48	16	$\sim 0.5 \cdot 10^3$
	k=1 (Dk=0.74)	3, 13, 14, 20, 19	0.62	1.53	15	$\sim 0.5 \cdot 10^3$

A comparative analysis of the author's methodology for predicting time series in the context of situational response and Cook's method produced the following results: in terms of the R2 criterion, the method based on data rejection is preferable. Cook's method trails to it by 10%; in terms of the magnitude of the displacement modulus of the forecast result, Cook's method turns out to be better. When rejecting such sets of measurements, the R2 magnitude sharply decreases (Cook's criterion is silent about this). This is due to the essence of Cook's criterion, which is aimed at blind (in case a computer is used) tracking of the minimum magnitude of the total Δi. In the machine version, Cook's criterion can be applied only together with the R2 criterion. Thus, our methodology offers better results for almost all criteria and is quite simple when applied in modern computer technologies, whereas Cook's method is difficult to formalize due to its great computational complexity and the lack of a formal criterion for identifying the impact of specific observations. When searching for anomalous values using the Acton method, a suspicious value Y =46,359 was found at X = 29,946, as the largest deviation of the initial measurements from the predicted data.

After that, the value was calculated and compared to the critical one. Since the calculated value turned out to be greater than the critical one, the value is recognized as a situational deformation. This method is intended for checking one suspicious value, but 2 more values were checked as an experiment. One of them turned out to be an outlier: Y=45,644.07 at X =32,285. Next, the Titien-Moore-Backman method was used to search for the anomalous value. A suspicious value was identified. The value obtained by the criterion was 2.71, but it turned out to be less than the critical value for the significance level of 0.1, so, according to this method, the suspicious value is not an outlier. The third was the Prescott–Lund method. We used it to obtain a value of 2.69, which is less than the critical value of 2.72. Therefore, this value is not recognized as an outlier. Figure 1 presents the results of the comparative analysis. As can be seen from the figure, the methodology proposed by the author is suitable for identifying a greater number of situational deformations in the time series compared to other methods. This result is achieved in 445 elementary operations.

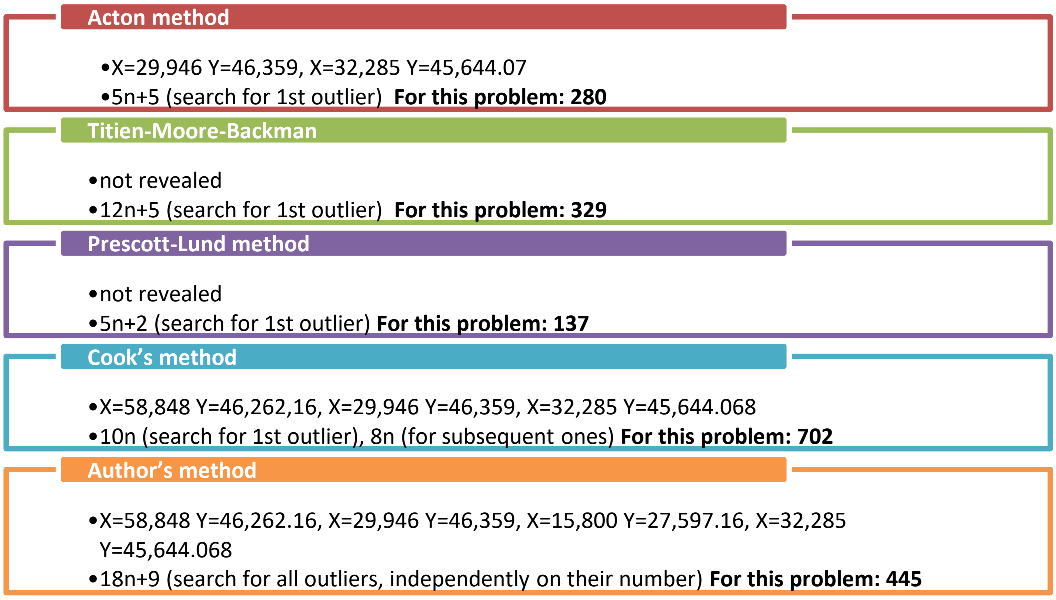

Figure 1 The results of a comparative analysis of the effectiveness of situational deformations determined using the most common methods (developed by Acton, Titien-Moore-Backman, Prescott-Lund, Cook) and the author's methodology for predicting time series in the context of situational response *(calculated by the authors).*

Two anomalous observations are detected by the Acton method, and none are detected by the Titien-Moore-Beckman or Prescott-Lund methods. Cook's method turned out to be the closest to our method in effectiveness. However, three situational deformations were identified using the former method. Besides that, the number of elementary operations grows if the number of suspicious values that are being checked is increasing. There is no specific criterion for which of the suspicious values should be recognized as deformations. Thus, the existing methodologies for predicting economic indicators in conditions of adaptation to various structural deformations have a number of serious drawbacks. Consequently, the methods used in the scientific literature have a number of common disadvantages, which can be eliminated if the author's methodology is applied: the methods are poorly formalized and adapt only to similar situational transformations at each step; most of them are used only for one-dimensional samples, i.e. there is a situational response only for one-time series; there are no specific recommendations on researcher's further actions after structural deformations have been found in the time series; common methods of responding to certain situations rely on specific laws of a probability distribution, and yet, they are not known at the initial level (Rodionov and Velichenkova, 2020; Lemeshko and Lemeshko, 2005). The methodology proposed by the author for improving the processing of initial statistical data and increasing the stability of linear regression models for more effective forecasts in the context of situational response offers a comprehensive approach to modeling and a capacity to smooth out situational deformations of time series as well as the level of seasonality.

6. Conclusions

The algorithm ensures better quality of economic forecasts obtained using linear regression models (from 15%), due to the preliminary processing of the source data and identification of the cyclic dominance of the modified series. In this case, the increase in the termination coefficient can be from 15% to 30% due to the process of data rejection and structural modifications. The study shows that the methodology for predicting time series in the context of situational response offers the fastest and most accurate data analysis procedure suitable for detecting any situational deformations. The author's methodology, which implies detection and further change of the measurement values, increases the stability of linear regression models and makes forecasts more effective in the context of situational response. It offers you a comprehensive approach to modeling where situational deformations of time series can be smoothed out, and the level of seasonality for samples of a small size is reduced because, unlike a method where the data is simply excluded, with this approach, the initial amount of data is preserved. The mathematical tools proposed in this paper for improving the stability of regression models are to be used in further research for nonlinear regression predictive equations with internal linearity based on structural transformations and reduction to a linear form.

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References

Agus, A.A., Yudoko, G., Mulyono, N., Imaniya, T., 2021. E-Commerce Performance, Digital Marketing Capability and Supply Chain Capability within E-Commerce Platform: Longitudinal Study Before and After COVID-19*. International Journal of Technology,* Volume 12(2), pp. 360–370

Babkin, A., Tashenova, L., Mamrayeva, D., Andreeva, T., 2021. A Structural Functional Model for Managing the Digital Potential of a Strategic Innovatively Active Industrial Cluster. *International Journal of Technology,* Volume 12(7), pp. 1359–1368

Boginsky, A.I., 2021. The Assessment of Technical and Economic Indicators of Products Formed Under the Influence of Inno-vative Technologies. *Lecture Notes in Networks and Systems.* Volume 280. pp. 53–62

Egorov, N., Babkin, A., Babkin, I., Yarygina, A., 2021. Innovative Development in Northern Russia Assessed by Triple Helix Model. *International Journal of Technology,* Volume 12(7), pp. 1387–1396

Grishunin, S., Naumova, E., Burova, E., Suloeva, S., Nekrasova, T., 2022. The Impact of Sustainability Disclosures on Value of Companies Following Digital Transformation Strategies. *International Journal of Technology*. Volume 13(7), pp. 1432–1441

Hao, Y., 2022. Effect of Economic Indicators, Renewable Energy Consumption and Human Development on Climate Change: An Empirical Analysis Based on Panel Data of Selected Countries. *Frontiers in Energy Research,* Volume 10, p. 841497

Kredina, A. Nurymova, S. Satybaldin, A. Kireyeva, A., 2022. Assessing The Relationship Between Non-Cash Payments and Various Economic Indicators. *Banks and Bank Systems.* Volume 17(1), pp. 67–79

Lemeshko, B.Y., Lemeshko, S.B., 2005. Extending the Application of Grubbs-Type Tests in Rejecting Anomalous Measurements. *Measurement Techniques.* Volume 48(6), pp. 536–547

Nazarychev, D.V., Marinin, S.A., Shamin, A.E., 2022. Topical Issues of Determining the Threshold Values of Indicators of Economic Security for Integrated Industrial Enterprises. *Lecture Notes in Networks and Systems,* Volume 372, pp. 751–760

Pishchalkina, I., Pishchalkin, D., Suloeva, S., 2022. Research of the Efficiency of Mining and Metallurgical Enterprises Based on the Environmental, Social, and Governance Risk Rating in the Context of Digital Transformation. *International Journal of Technology. Volume 13(7)*, pp. 1442–1451

Prasetya, B., Yopi, Tampubolon, B.D., 2023. Role of Risk Management and Standardization for supporting Innovation in New Normal based on Lessons Learned during Pandemic COVID-19. *International Journal of Technology*. Volume 14(5), pp. 954–971

Rodionov, D., Velichenkova, D., 2020, Relation Between Russian Universities And Regional Innovation Development. *Journal of Open Innovation: Technology, Market, and Complexity.* Volume 6(4), pp. 1–26

Rusanov, M.A., Abbazov V.R., Baluev, V. A., 2022. On The Approach to Forecasting Indicators of Socio-Economic Devel-Opment of The Region Based on Indirect Indicators. *Modeling, Optimization and Information Technology.* Volume 38, pp. 2–3

Sandler, D., Gladyrev, D., 2020. Analysis of The Relations Between Scientometric And Economic Indicators of Russian Universities' Performance. *Business, Management and Education*, Volume 18(2), pp. 331–343

Saroji, G., Berawi, M.A., Sari, M., Madyaningarum, N., Socaningrum, J.F., Susantono, B., Woodhead, R., 2022. Optimizing the Development of Power Generation to Increase the Utilization of Renewable Energy Sources. *International Journal of Technology. Volume* 13(7), pp. 1422–1431

Tanina, A., Ivanova, M., Kulkaev, G., Tanin, E., 2022. Model of State Support for The Digital Transformation of The Manufacturing Industry in Russian Regions. *International Journal of Technology*, Volume 13(7), pp. 1538–1547

Zainy, M.L.S., Pratama, G.B., Kurnianto, R.R., Iridiastadi, H., 2023. Fatigue Among Indonesian Commercial Vehicle Drivers: A Study Examining Changes in Subjective Responses and Ocular Indicators*. International Journal of Technology,* Volume 14(5), pp. 1039–1048

Zaytsev, A., Dmitriev, N., Rodionov, D., Magradze, T., 2021. Assessment of the Innovative Potential of Alternative Energy in the Context of the Transition to the Circular Economy. *International Journal of Technology.* Volume 12(7), pp. 1328–1338

Zhogova, E., Zaborovskaia, O.Nadezhina, O., 2020. An analysis of the Indicators of Regional Economy Spatial Development in the Leningrad Region of Russia. *International Journal of Technology,* Volume 11(8), pp. 1509–1518

Zubkova, D.A., Rakova, V.V., Burlutskaya, Z.V., Gintciak, A.M., 2022. Automatic Calibration of Sociotechnical Systems Simulation Models on The Example of The Infection Spread Model . *International Journal of Technology,* Volume 13(7), pp. 1452–1462