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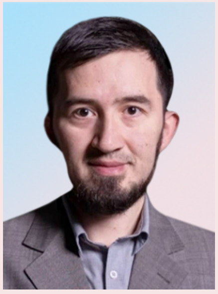
Assessing the Impact of Artificial Intelligence on Russian Labor Market Development Scenarios: Industry Analysis



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Abstract. Artificial intelligence has become an essential element of technological progress, while generative artificial intelligence occupies a special place as an innovative general-purpose technology. Given the rapid development of this technology and its high potential for mass adoption in various economic sectors, it becomes important to assess the impact of this technology on the labor market. The modern Russian labor market is characterized by low unemployment, staff shortages, and intersectoral imbalances. An urgent scientific task is to model scenarios for the development of the labor market in the context of sectors, taking into account the influence of generative artificial intelligence. The aim of the work is to assess the potential impact of the mass use of generative artificial intelligence on the labor market, due to changes in labor efficiency in some professions and industries, based on the analysis of statistical and expert data and economic and mathematical modeling of possible scenarios for the development of the labor market. Economic sectors were divided into three groups depending on the rate of change in personnel needs, based on the analysis of the Beveridge curve, which shows the dependence of the level of needs on the unemployment rate. Using existing statistical data and expert assessments, we determine the degree of influence of generative artificial intelligence on labor efficiency in various industries. We put forward an approach that helps to obtain estimates of possible scenarios for the development of sectoral labor markets for the period up to 2030, based on official forecasts of ministries (Ministry of Economic Development of the Russian Federation, Ministry of Labor of the Russian Federation) for the period up to 2026, their extrapolation, and superimposition of the impact of mass use of generative artificial intelligence (as a disturbing effect). The results obtained suggest that the severity of staff shortage issue in general can be partially reduced by using generative artificial intelligence; thus, we identified industries in which (a) it is possible to address the problem of staff shortage at the current level of needs, and (b) staff shortage will persist. Modeling the migration of professions and personnel between industries seems promising, because the expected effect of mass technology adoption will not only change the balance of labor resources, but also lead to the need to re-profile some of the personnel.

Key words: general-purpose technology, generative artificial intelligence, large language models, labor market, personnel shortage, scenario modeling.

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Introduction

Automation and robotization processes are not something new to the modern economy, but automation capabilities are reaching a whole new level with the emergence of new technologies such as generative artificial intelligence (AI). These technologies make it possible to automate processes that were previously considered solely the prerogative of humans. For example, generative AI can be used to create content, not only in the form of text, but also pictures, video, and sound, which significantly expands the application horizons of automation. In the study, generative AI primarily refers to models that work with text, i.e., large language models. Generative AI has significant potential to improve performance in various fields by fundamentally changing some part of work processes and enhancing human capabilities. There are studies (Gambacorta et al., 2024) that have shown a 55% increase in programmers' productivity through the use of generative AI. If there are algorithizable, often repetitive tasks in which the risk of error is not critical, generative models can do part of the work, including creating draft texts, codes or design, analyzing a large amount of information, speeding up work processes, for example, in accounting, marketing, HR, etc.

Currently, the Russian labor market is experiencing a personnel shortage. According to Rosstat, in July 2024, the unemployment rate is at a historic low of 2.4%. There is a need to analyze the existing trends in the labor market, develop labor market development scenarios and identify factors that can reduce the negative impact of staff shortage, including through generative AI.

On the one hand, low unemployment may indicate an approach to full employment, when the country's labor resources are used to the maximum, but there is a risk of negative effects. In the absence of sufficient free labor resources in the labor market, the enterprises' development may slow down. R.I. Kapeliushnikov states that "the Russian economy will have to operate for a long time in stressful conditions of acute shortage of labor resources, which threatens to become the main brake on its sustainable growth" (Kapeliushnikov, 2024). To overcome this situation, in an attempt to compensate for labor shortages, companies may increase the workload of existing employees or have to resort to wage increases as employers compete for a limited number of employees. This will obviously increase the costs associated with hiring, training and retaining employees. In general, wage increases not only lead to inflationary pressures, but also to higher inequality of working conditions, increasing social and economic inequality. There are risks that employers may have to hire less skilled or less productive workers just to fill vacancies, which can reduce overall productivity, and many employees may become less motivated to develop professionally, knowing that they can easily find a job even without upgrading their skills. Employees may also change jobs more frequently in search of better working conditions, higher wages, or better benefits, knowing that there is a labor shortage in the labor market.

The aim of the study is to assess the potential impact of generative artificial intelligence on the labor market in the context of economic sectors through changes in labor efficiency, based on data analysis and economic and mathematical modeling of possible scenarios of labor market development.

Literature analysis

One of the tools for analyzing the labor market is the construction of the Beveridge curve, which describes the relationship between the unemployment rate and the vacancy rate (Alekhin, 2024; Kapelyushnikov, 2024). The Beveridge curve is a tool to assess the "productive capacity" of the labor market. Maximum labor efficiency is the case when the curve is minimally distant from the origin of coordinates (Kapelyushnikov, 2024). "The Beveridge curve has become a central concept in labor market macroeconomics also because it has two advantages. First, each value of the empirical curve indicates the state the economy is in at a given point in time. Second, the empirical curve allows separating changes in the labor market system due to shocks to the activity of economic agents from its changes due to structural shocks" (Alekhin, 2024).

"When the unemployed are few and the demand for labor is high, it is difficult for employers to find additional labor, even if they increase the number of vacancies. And vice versa, when the unemployed are many and vacancies are few, each vacancy is quickly replaced, which strongly affects the unemployment rate" (Alekhin, 2024). At the same time, the analysis of the Beveridge curve, which in fact reflects the dependence of only two indicators, should not be limited to conclusions on them. Indeed, the number of actual vacancies, for example, depends not only on the needs of enterprises, but also on the speed of their closure, which in turn depends on many factors, including the level of wages, working conditions, readiness of the population to structural changes in the labor market, relocation, etc.

B.I. Alekhin highlights the following advantages of the analysis of the empirical Beveridge curve: "It is more convenient to interpret the Beveridge curve to assess the labor market conditions than to analyze two separate time series –vacancies and unemployed"; "by the points of the Beveridge curve, it is possible to determine the current state of the economy", i.e. the state of economic recession or expansion; "the Beveridge curve helps to distinguish changes in the market system of employment caused by business activity from changes caused by structural shocks". "Thus, an economy moving from recession to expansion and back again leaves a trail of dots along the trend line. Recession and unemployment are mutually reinforcing. But, as the U.S. Federal Reserve once stated, unemployment "rises like a rocket and falls like a feather" (Alekhine, 2024).

The Beveridge curve can vary across industries due to differences in labor demand, technological change, seasonal fluctuations, and institutional factors. For example, the introduction of new technologies may reduce jobs in industry but create them in the IT sector. Seasonal fluctuations particularly affect agriculture and construction. The skill level of workers and their mobility requirements also play an important role, as training time for different industries can vary widely. For example, an increase in demand for physicians and their wages may not increase their numbers if there are no unemployed physicians in the labor market. In addition, economic cycles affect industries differently: manufacturing and construction are hit hard during recessions, while health care and education are more stable. Social and demographic changes can also lead to differences (Bonthuis et al., 2016; Destefanis et al., 2020).

Researchers have applied different models and methods to assess the impact of generative AI on the labor market. Many of the methods are based on earlier studies. Generative AI is not the first technology that has led to changes in the labor market, and in choosing a methodology to assess the impact of generative AI on the labor market, researchers often rely on methodologies that have been used previously to assess changes due to other factors. It is worth noting the method based on the assessment of the possibility of automating individual tasks by their textual description and the method of analogies in terms of methods for assessing the impact of generative AI on the labor market.

Method for evaluating the automation of individual tasks by their textual description. The methodology is based on the use of verb-noun pairs describing specific labor functions. Webb (Webb, 2019) describes the application of this methodology to analyze task automation. It offers a structured approach to identifying tasks that can be automated by generative AI, including data collection, comparison with technologies, expert judgment, and calculation of automation probability.

The article "The Economics of Generative AI" (NBER) (Brynjolfsson, Li, 2024) notes that generative AI increases productivity through task automation. The paper describes the Productivity J-Curve model, showing the time lag between technology adoption and productivity growth. The authors used O*NET data and AI patents to analyze the impact of generative AI on occupations, revealing that 80% of the US workforce can be impacted by task automation through large language models such as ChatGPT-4.

Task and impact analysis methodology. The methodology assesses which tasks can be automated by AI and how this will affect occupations. The article (Eloundou et al., 2023) discusses the impact of large language models on the labor market, analyzing the impact of AI on different tasks.

Method of analogies for forecasting staffing needs and assessing the impact of AI on the labor market. The method of analogies predicts staffing needs and evaluates the impact of AI on the labor market by analyzing similar situations. Enhancing Work Productivity through Generative Artificial Intelligence: A Comprehensive Literature Review (Al Naqbi et al., 2024) examines the impact of generative AI on labor productivity using historical analogy and bibliometric analysis.

The paper "Forecasting Human Resource Needs for Artificial Intelligence in Russia" (Averyanov et al., 2023) applies the method of analogies to assess the human resource needs in the AI field. It is used to forecast future changes in the labor market based on analogies with other technological transformations.

The methods are often difficult to categorize into a single methodology. The article (Averyanov et al., 2023) applies elements of the labor balance method and the method of analogies to provide a comprehensive analysis. The labor balance method estimates the distribution of labor resources, while the analogy method predicts labor demand based on similar situations, providing conclusions about the future demand for workers in the AI industry.

The spread of any general-purpose technology, including generative AI, causes the transformation of the labor market and raises a number of issues related to its structural reorganization and changes in the ratios of labor performed by humans and performed by machines. The problem of technological unemployment emerges in a new capacity, accelerating the process of displacement of human labor in many industries (Kolade, Owoseni, 2022).

Important questions arise about the future of employment, its quality and income distribution as machines and algorithms increasingly perform tasks that were once part of human labor. The article “The Impact of Industry 4.0 and Digitalization on the Labor Market in 2030 – Confirming Keynes’s Prediction” (Szabó-Szentgróti et al, 2022) notes that, on the one hand, the extent of technological unemployment will largely depend on the digitalization strategy adopted in each country, the speed of its implementation, and the readiness of the country’s education system to retrain vulnerable groups of working-age population; on the other hand, the amount of necessary work tasks will decrease, bringing us closer to Keynes’s concept of three working hours per day. At the same time, the reduction of working hours will increase economic efficiency through more intensive and efficient work (Gachaev et al., 2023).

Current scientific research shows that shortening the work week can bring significant benefits to employees and organizations. For example, a UK study[1] found that moving to a four-day working week led to a significant reduction in employee stress and sick days, while productivity remained the same. Therefore, employers, on the one hand, may intentionally and formally reduce the length of the working week, on the other hand, this may occur covertly. In such cases, an employer may be aware that an employee does not actually work a full 40-hour week, taking into account, for example, remote or hybrid forms of work, the use of generative AI, but he or she agrees to it, forming a loyal attitude of the employee to themselves and ensuring the fulfillment of necessary work tasks. In this context, the use of generative AI opens up a wide range of opportunities to improve the quality of life, but becomes an inevitable element of competition by reducing marginal costs (Sulumov, 2022).

A number of researchers also note that the spread of generative AI will necessitate the creation of new professions and new jobs, the number of which may be comparable or greater than the number of jobs in which humans will be replaced by machines in the digital transformation of the economy (Panetta, 2017).

Analysis of the current state of generative AI utilization shows that the possible options for the potential impact of generative AI can be summarized into the following development scenarios:

1) reduction in working hours or workweek by increasing labor productivity with generative AI (Gupta et al., 2024; Ellingrud et al., 2023);

2) unemployment increase in the short term; decrease in the number of jobs due to the ability of generative AI to replace some labor functions (Autor, 2022; Haapanala et al., 2023; Brynjolfsson et al., 2023);

3) employment growth in the long term due to the impact of generative AI potential on economic growth; economic growth in turn will be associated with the development and implementation of modern technologies, and possible negative effects will be overlapped with positive ones (Broecke, 2023; Kalish et al., 2023; Al Naqbi et al., 2024).

At the same time, all researchers, despite which scenarios they consider more likely, note the presence of trends toward changes in professional competencies and labor functions, because some of them will be replaced by modern technologies, and some will require development, to a greater or lesser extent, depending on the field of activity. One way or another, there will be a change in the balance of labor resources.

[1] University of Cambridge. Working a four-day week boosts employee wellbeing while preserving productivity, major six-month trial finds. ScienceDaily, 21 February 2023. Available at: https://www.sciencedaily.com/releases/2023/02/230221113132.htm

Despite the literature on the impact of automation on the labor market in Russia (Gimpelson, Kapeliushnikov, 2022; Kapeliushnikov, 2024), there are no works on assessing the impact of generative AI, automation is considered as “replacement of labor by machines or artificial intelligence with the elimination of relevant jobs” and “in the foreseeable future is unlikely to be realized” (Gimpelson, 2022). In our study, however, generative AI is considered not as a tool for replacing human labor, but as a tool for increasing the labor efficiency (productivity). Automation, according to the estimates of V.E. Gimpelson and R.I. Kapeliushnikov, will affect about 10% of the employed: “Calculations show that the total share of jobs where routine operations prevail is small and amounts to a little more than 10%” (Gimpelson, Kapeliushnikov, 2022), while in our study the estimates of the impact of technology on individual industries (e.g., IT) reach 50%, and the average for the economy is 23%.

The increase in labor productivity due to the mass introduction of generative AI technology is only one of the factors affecting the labor market development. Our study only indirectly takes into account all factors (demography, migration policy, geopolitical situation, state of the economy, labor productivity, share of wages in GDP and others), by using the official forecasts of the Ministry of Labor and Ministry of Economic Development, taken as an inertial scenario.

Methodology of the research

The research methodology is based on our approach to assessing the generative impact AI on the staff shortage and gross domestic product (GDP) in various economy’s sectors *(Fig. 1)*. The following tasks can be considered as the enlarged stages of the research:

1) assessment of the current state of the labor market (staff shortage) through the construction of the Beveridge curves; for the study, we used Rosstat data on output, employment, personnel needs and unemployment rates;

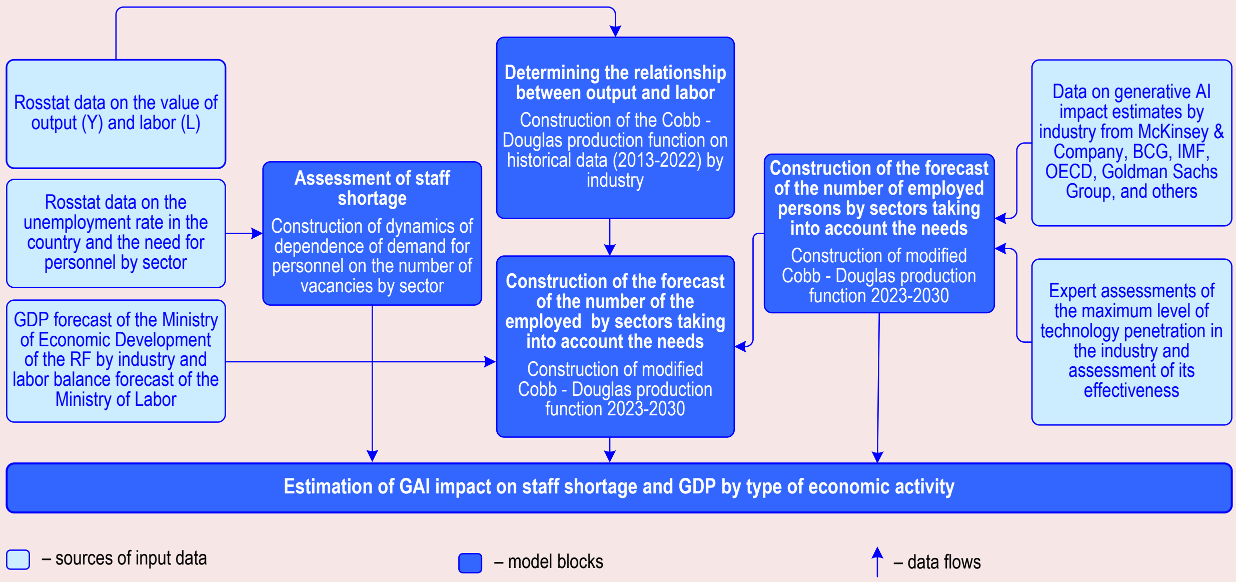
2) construction of an econometric model of the relationship between output and labor values based on statistical data for the period 2017–2022;

3) construction of dependence up to 2027 based on official GDP forecasts provided by the Ministry of Economic Development and labor balance forecasts from the Ministry of Labor, and then extrapolation of the inertial forecast up to 2030;

4) assessment of the impact of generative AI on labor productivity based on estimates of the possible increase in labor productivity, taking into account different levels of technology penetration (share of users from the number of employees) in the industry and different efficiency of the technology. It means that the approach of Acemoglu, Restrepo (Acemoglu, Restrepo, 2018) is applied, where it is considered that there is a part of labor resources (a)whose efficiency can be improved by an amount (k), and then the number of employed L by efficiency works as $L^*=akL+(1-a)L$. Estimates of the generative AI impact on labor productivity and the economy are taken from reports of such sources as IMF, OECD, McKinsey & Company, BCG, etc., which are supplemented by expert scenarios using simulation-expert modeling[2], when existing trends in the development of sustainable indicators on the basis of a computational simulation model are iteratively adjusted with the help of expert estimates.

[2] Ototskii P.L. (2008). Mathematical model of the socio-economic system of the region taking into account external disturbing influences: specialty “Mathematical modeling, numerical methods and program complexes”: Candidate of Sciences (Physics and Mathematsl) thesis. Moscow. 132 p.

Figure 1. Model Architecture



The research (Alekhin, 2024; Kapeliushnikov, 2024) uses the Beveridge curve to analyze the relationship between the unemployment rate and the number of vacancies, which shows the inverse relationship between the unemployment rate and the number of vacancies and helps to understand the labor market state. The article “Expansion of Vacant Jobs in the Russian Labor Market: Dynamics, Composition, Triggers” (Kapeliushnikov, 2024) notes that during the last few years the unsatisfied demand for labor force reached a record high by the standards of the Russian labor market, which caused the Beveridge curve to shift sharply upward.

We used Rosstat data on the dynamics of the unemployment rate and staffing needs by industry to assess the staff shortage. The obtained functions of dependence between the unemployment rate and the number of vacancies by industries allow comparing industries in terms of the dynamics of personnel needs.

Low unemployment indicates high demand for labor and staff shortage, which creates difficulties for employers in hiring qualified workers. Under such conditions, employers are forced to look for alternative solutions to maintain production levels and meet market demands. One such solution is to replace human labor with technology.

The Cobb – Douglas function can be used to analyze production processes and estimate the contribution of labor and capital to economic output. In the context of labor shortages and low unemployment, employers are increasingly turning to technology to compensate for labor shortages. To more accurately account for the current factors affecting productivity, we propose to modify the Cobb – Douglas function by adding an automation factor associated with the introduction of generative AI, which makes it possible to account for the impact of new technologies on output. This is especially important in a rapidly changing labor market, where generative AI can significantly reduce the dependence of output on the number of workers and increase overall production efficiency. When moving from a classical production function to a modified one that allows taking into account the impact of generative AI on different industries, there is a need to quantify the degree of technology penetration in the industry (what percentage of those employed in the industry will use it) and to estimate the labor efficiency improvement indicator (how much labor productivity will increase).

When forming the inertial forecast, we used official forecasts of ministries (Ministry of Economic Development of the RF, Ministry of Labor of the RF) up to 2026; then we extrapolated the forecasts and superimposed the assessment of changes in the inertial scenario under the influence of generative AI technology (as a perturbing influence): "Forecast of long-term socio-economic development of the Russian Federation for the period until 2030" and the current forecast of socio-economic development of the Russian Federation for 2024 and for the planning period of 2025 and 2026 of the Ministry of Economic Development of the RF, the latter of which is updated annually, forecasts of the Ministry of Labor of the RF, in particular "Forecast of the balance of labor resources for 2024–2026". The Ministry of Economic Development provides not only forecast scenarios (baseline and conservative) for the main macroeconomic indicators, including GDP, investment in fixed capital, etc., but also forecasts for the structure of GDP by sector.

Based on the estimates of the degree of technology penetration in the industry and the labor efficiency improvement indicator, we can determine the degree of influence of generative AI on the labor market for each of the industries. There arises the possibility of using a scenario approach and parametric simulation modeling, when in the described system we can estimate the necessary level of technology penetration to obtain a certain specified effect, or, conversely, estimate the possible effect taking into account the assumptions about the level of technology penetration, as well as model several scenarios by varying the values of the mentioned values as a parameter. As a result, scenarios of labor market changes will be proposed taking into account the application of generative AI technology, including changes in the number of vacancies, based on data analysis and economic and mathematical modeling of possible labor market development scenarios.

Assessment of labor shortage

The analysis of the ratio of supply and demand in the labor market through the indicators of the need for personnel (number of vacancies) by sectors and the unemployment rate indicates personnel shortage. Indeed, the decrease in the unemployment rate and the increase in the demand for personnel led to the fact that the level of demand exceeded the unemployment rate, and in a number of industries more than 3 times, while "in most developed countries the equilibrium ratio of vacancies to unemployment is in the range of 0.7–1.0"[3], i.e. the number of vacancies does not exceed the unemployment rate. That is, the number of vacancies does not exceed the unemployment rate. "Values consistently exceeding this range indicate structural imbalances in the labor market"[4]. We consider the dynamics of indicators (from the first quarter of 2022 to the second quarter of 2024) to analyze trends, construct the Beveridge curve for each of the industries. *Figure 2* shows the Beveridge curve for total demand by A-S industries,

[3] OECD Employment Outlook 2022: Building Back More Inclusive Labour Markets. OECD Publishing, Paris.

[4] Ibidem.

Figure 2. Beveridge curve for aggregate data

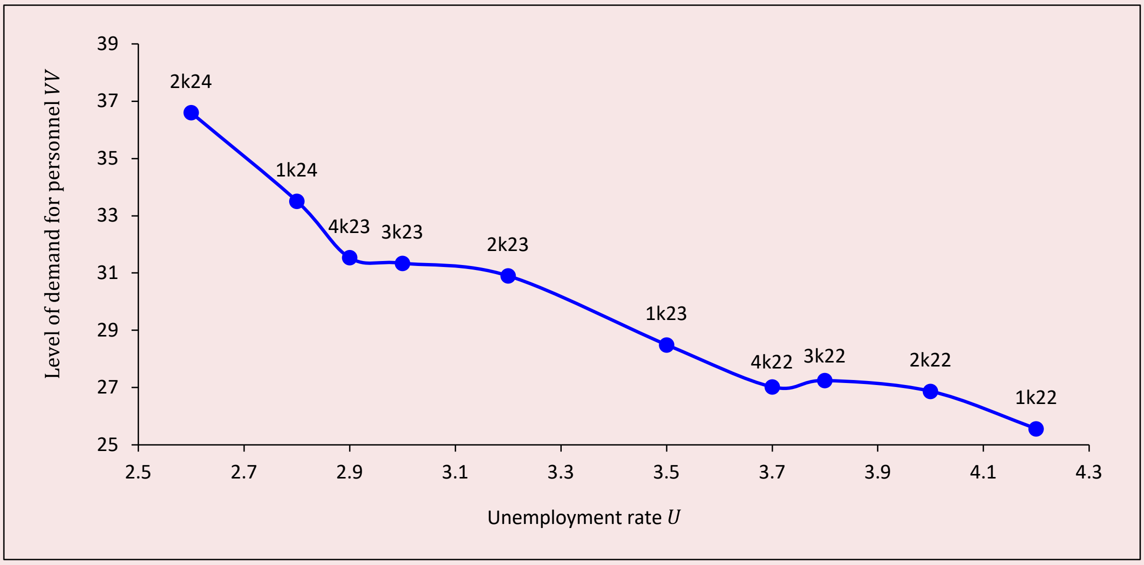
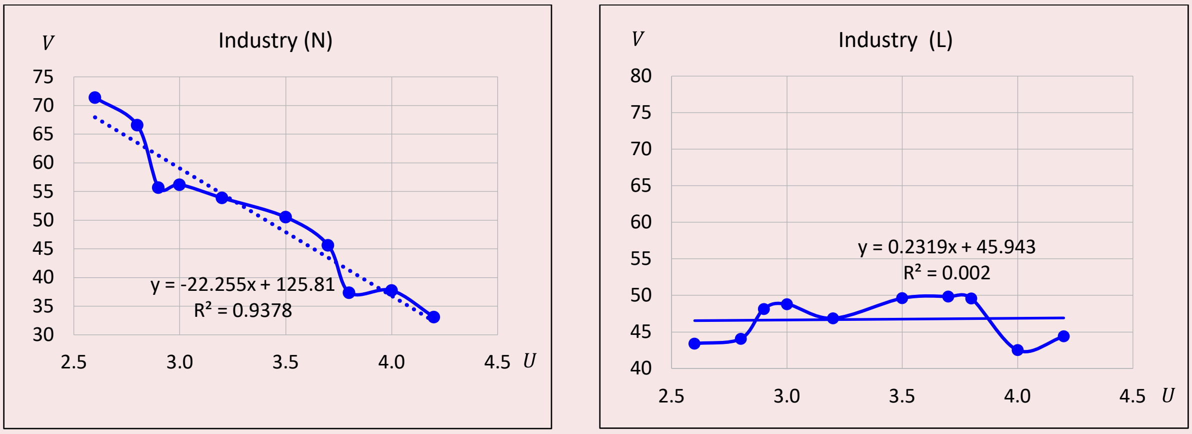


Figure 3. Beveridge curves for industries N (left) and L (right)



and *Figure 3* gives examples of industries with different rates of change in demand: industry (N) (administrative and related additional services) as an example of an industry where the unemployment growth led to a multiple increase in the level of demand for human resources (more than 2 times), and industry (L) (real estate activities) as an example of an industry where the growth of demand was not observed. For calculation we used official data of Rosstat on unemployment rates in % and levels of demand for personnel, V – number of vacancies per 1,000 employed (we used the ratio of the number of required employees on the list for vacant jobs at the end of the reporting quarter to the number of employed in the industry according to Rosstat data). We made calculations for 10 quarters, from the first quarter of 2022 to the second quarter of 2024.

Table 1 presents the computational results, obtained by the least squares method to estimate the formula coefficients:

$$V = b_0 + b_1 \cdot U,$$

where V is the industry's demand for personnel,
U is the unemployment rate,
b_0, b_1 are unknown coefficients.

Thus, the ranking of industries depending on the rate of change in human resources needs (based on the Beveridge curves) allowed identifying industries with high growth rates of human resources needs. These industries are most affected by changes in labor productivity, which makes them the most promising for the introduction of generative AI. However, it is important to keep in mind that the speed of technology adoption will be determined by both industry demand and the technical capabilities of generative AI to improve labor productivity. For example, in industries with a high proportion of routine tasks, such as finance or IT, generative AI can improve labor productivity faster than in industries with low automation, such as agriculture. Ranking industries by the rate of change in labor needs allows the government to better design and implement policies on employment, education, and technological development. This helps to focus efforts on those sectors where the shortage of human resources is most critical and where the introduction of technologies such as generative AI can have the maximum effect. For a more accurate assessment of the impact of generative AI on labor productivity, it is necessary to build a forecast of labor market development taking into account the peculiarities of each industry.

Building an inertial forecast of the labor market development

The apparatus of production functions is usually used to assess the potential for technology impact (Jones, 2016; Vavilova, Rayan, 2024).

$$Y = AK^{\alpha}L^{\beta}$$

Table 1. Ranking of industries depending on the rate of change in personnel needs changes in human resources needs

Description of industry group	Industry	Coefficient b_1
A 0.1% increase in unemployment led to a 0.9% or more increase in the need rate	Water supply; wastewater disposal, organization of waste collection and utilization, pollution elimination activities (E)	-24.205
	Administrative activities and related ancillary services (N)	-22.255
	Manufacturing industries (C)	-10.88
	Provision of electricity, gas and steam; air conditioning (D)	-10.497
	Wholesale and retail trade; repair of motor vehicles and motorcycles (G)	-9.3103
A 0.1% increase in unemployment led to a 0.1–0.9% increase in the need rate	Public administration and military security; social security (O)	-6.6452
	Mining and quarrying (B)	-5.0797
	Agriculture, forestry, hunting, fishing and fish farming (A)	-5.067
	Transportation and storage (H)	-4.8209
	Building (F)	-4.3137
	Education (P)	-2.6172
	Information and communication activities (J)	-2.5889
	Professional, scientific and technical activities (M)	-1.9203
	Activities in the field of culture, sport, leisure and entertainment (R)	-1.571
	Activities of hotels and catering companies (I)	-1.2212
The increase in need is minimal, a 0.1% increase in unemployment resulted in a less than 0.1% increase in the level of need	Provision of other services (S)	-0.6985
	Health and social services activities (Q)	-0.4052
	Real estate activities (L)	0.2319
	Financial and insurance activities (K)	1.3308

The construction of the Cobb – Douglas function in the context industries allows taking into account the specifics of industries. The classical approach faces the problem of data endogeneity, when capital and labor are correlated with the model error, which leads to biased estimates. This can be caused by several reasons, the main ones being correlation between capital and labor or non-stationarity of the data, presence of unaccounted feedbacks, e.g. not only output grows from the value of capital but also capital grows from the value of output, measurement errors, etc. Construction of inertial forecast of the labor market development. For example, calculations of the coefficients of the equation $Y = AK^{\alpha}L^{\beta}$ for the industry "real estate activities" showed a negative degree of β (when the number of employees decreased and gross value added increased), and when imposing the constraint $\alpha + \beta = 1$, which is usually interpreted as a condition of constant returns to scale, $\beta = 0$. This result may lead to false conclusions about the independence of output from employment or about the presence of an inverse relationship. Similar results for other industries are associated with the effect of multicollinearity, endogeneity, and sometimes with low variability of the number of employees. Construction of inertial forecast of the labor market development. The values of labor and capital in economic data are often difficult to use in their original form because they are non-stationary and endogenous with respect to the model. This means that their levels can change over time due to factors such as economic growth, investment, demographic change and technological innovation. Typically, capital and labor indicators have trends, making their time series non-stationary. To use the data correctly, econometric modeling often employs techniques such as cointegration checks and transformation of the data (e.g., differences) to make them stationary.

A constraint is often imposed: the sum of degrees in the Cobb – Douglas function is equal to one $\alpha + \beta = 1$. This is usually interpreted as a condition of constant returns to scale. This study has shown that it is possible to improve the quality of the estimates of the Cobb – Douglas function by using an approach where both parts of the equation are divided by the value of the number of people employed (Jones, 2016). In essence, this approach allows study labor productivity (in the sense of the ratio of output to employment), excluding the impact of the total number of workers and focusing on the returns to capital and technology.

$$\frac{Y}{L} = \frac{AK^{\alpha}L^{1-\alpha}}{L} = \frac{AK^{\alpha}}{L^{\alpha}} = A(\frac{K}{L})^{\alpha}$$

It is revealed how this indicator depends on time based on the statistical analysis of the dynamics of the ratio $\frac{Y}{L} = f(t)$. *Figure 4* shows an example of plotting the graph for the industry (C) "Manufacturing". Given this, we can use this property of the function to forecast the ratio in future periods by selecting the coefficients of the function $P = f(t)$ on the known data and then extrapolating the values.

In our case, the estimation was made on the data from 2017 to 2022. The values of gross value added (GVA) by industry (in 2021 prices) were used as the value of output Y by industry, and the value of labor resources L – the number of employed persons by economic activity. Thus, using the method of least squares we obtain equations for the inertial forecast of $\frac{Y}{L}$ values for all industries with appropriate values of model quality (coefficients of determination R^2) (*Tab. 2*) and the possibility to use one of the variables as a parameter for scenario modeling of the second variable, i.e. to have estimates of output values depending on the estimated values of the number of employees and vice versa.

$$Y = PL$$

Figure 4. Graph of $\frac{Y}{L}$ ratio by industry (C) "Manufacturing"

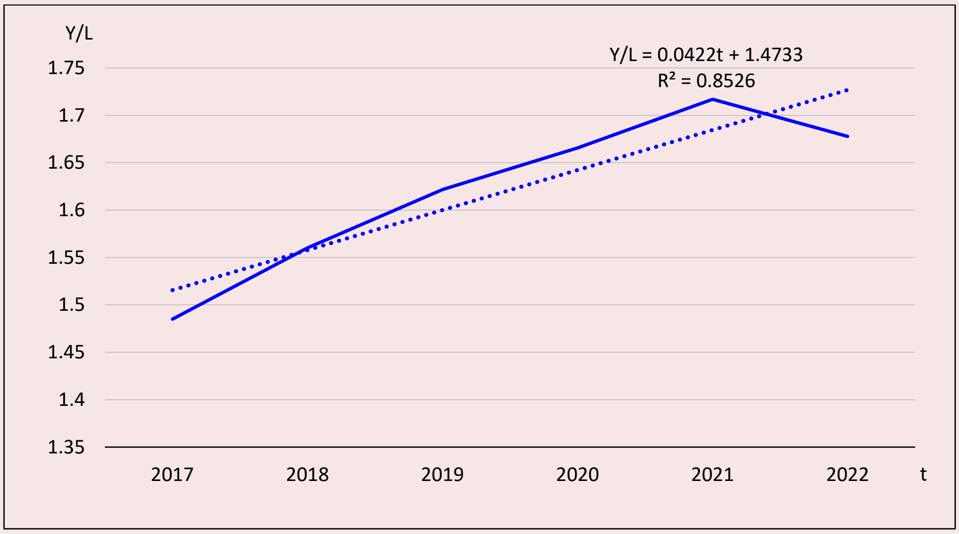


Table 2. Equations of dynamics of Y/L ratio

Industry	Equation	Coefficient of determination R^2
Agriculture, forestry (A)	Y/L = 0.0554t + 0.9373	R^2 = 0.9833
Mining and quarrying (B)	Y/L = -0.1214t + 14.369	R^2 = 0.4538
Manufacturing industries (C)	Y/L = 0.0422t + 1.4733	R^2 = 0.8526
Provision of electricity, gas and steam; air conditioning (D)	Y/L = 0.1155t + 1.2858	R^2 = 0.8908
Водоснабжение; водоотведение, организация сбора и утилизации отходов (E)	Y/L = 0.0273t + 0.7042	R^2 = 0.8469
Building (F)	Y/L = 0.0058t + 0.8899	R^2 = 0.2528
Wholesale and retail trade; repair of motor vehicles and motorcycles (G)	Y/L = 0.0008t + 1.1428	R^2 = 0.0008
Transportation and storage (H)	Y/L = -0.0307t + 1.4976	R^2 = 0.5827
Activities of hotels and catering companies (I)	Y/L = -0.0087t + 0.5974	R^2 = 0.0935
Information and communication activities (J)	Y/L = 0.0721t + 1.7986	R^2 = 0.8782
Financial and insurance activities (K)	Y/L = 0.488t + 2.3556	R^2 = 0.9754
Real estate activities (L)	Y/L = 0.1601t + 5.852	R^2 = 0.9693
Professional, scientific and technical activities (M)	Y/L = 0.0704t + 1.5051	R^2 = 0.9317
Administrative activities and related ancillary services (N)	Y/L = -0.0271t + 1.4079	R^2 = 0.6924
Public administration and military security; social security (O)	Y/L = 0.0813t + 1.9488	R^2 = 0.8192
Education (P)	Y/L = 0.0025t + 0.6841	R^2 = 0.2058
Health and social services activities (Q)	Y/L = 0.0198t + 0.8399	R^2 = 0.5891
Activities in the field of culture, sport, leisure and entertainment (R)	Y/L = 0.0283t + 0.8703	R^2 = 0.5452
Provision of other services (S)	Y/L = 0.0056t + 0.343	R^2 = 0.3488

The use of the proposed approach allowed obtaining equations with high coefficients of determination (more than 0.8) for most industries. Low values of the coefficients of determination (less than 0.5) were obtained only in such industries as construction (as an industry sensitive to changes in the economy), as well as in industries affected by the coronavirus pandemic (trade, hotels and catering, and education) and which are highly dependent on external factors (mining).

Building a forecast of labor market development taking into account the impact of generative AI technology

Next, we focus on the assessment of changes in output indicators under the impact of the introduction of generative AI technology, taking into account the need to analyze the existing cause-and-effect relationships. It is obvious that if generative AI is able to automate some labor functions, then first of all it is necessary to determine the impact of the technology on labor productivity. The need arises to introduce the concept of "effective number of employees" or "effective number of employees". If the efficiency of an employee grows by 1+ k times, then we will say that k is a parameter that shows the level of efficiency (productivity) increase due to the use of generative AI and the new total productivity of the same number of employees, increased only due to generative AI, will be called the effective number of employees. The degree of penetration of the technology should also be taken into account. The efficiency will definitely vary from industry to industry, since different industries have different numbers of tasks that will be affected by generative AI (Ototskii, Pospelova, 2024).

In the article "Artificial Intelligence, Automation, and Work" (Acemoglu, Restrepo, 2018), the authors use the following classical production function, dividing labor into automatable and non-automatable tasks $Y = f(L, K, A)$, where: Y is total output, L is labor (total labor input), K is capital, and A is the level of automation. The production function can be disaggregated to account for automated (M) and non-automated (N) tasks $Y = f(M, N, K)$, where M – tasks that can be automated, N – tasks that cannot be automated.

If we consider generative AI as one way of automating labor, we can use the approach of (Acemoglu, Restrepo, 2018) to modify the $Y = PL$ formula to account for the impact of generative AI:

$$Y^* = PL^* = P(akL + (1 - a)L),$$

where a is the penetration rate of generative AI in an industry; industry penetration rate refers to the share of employees using generative AI in their work; it is clear that depending on the industry there will be a different penetration rate of the technology, because this indicator characterizes the share of automated tasks, and the penetration rate is far from 100%; even in the industry "information and communication activities" it is assumed that it will not exceed 50% by 2030, and in some industries, such as agriculture, construction, etc.,

k – efficiency (productivity) increase due to the use of generative AI. The coefficient is set as a constant, because in the framework of this work the potential impact of technology was assessed taking into account its current level of development. There are three main points of view regarding the further speed of technology development:

1) continued rapid development to strong AI; Mira Murati (chief technology officer of OpenAI) stated that GPT-5 intelligence will reach PhD level in 2025/2026;

2) saturation of the intelligence level of generative AI at the current level given the utilization of current neural network architecture, data volumes, and available computing power (Widder, Hicks, 2024);

3) AI disillusionment hypothesis and the transition to a "third AI winter" with a decline in the technology's popularity (Cahn, 2024).

Due to the high degree of uncertainty, the task of technology development forecasting is left out of this study. The second hypothesis is accepted (saturation of the technology level at the current level), we estimate the economic effect of mass application of the technology in the form in which it is currently available.

We took McKinsey's estimates of ak as the effect of generative AI in the industry as the basis for the estimates[5]. Then, for each industry, we expertly determined the value of k taking into account the experience of Russian companies and existing studies[6]. Based on this, the initial values of a were estimated. We model the dynamics of changes in the value of a in the period from 2023 to 2030 by a logistic curve, with the maximum values also set by experts.

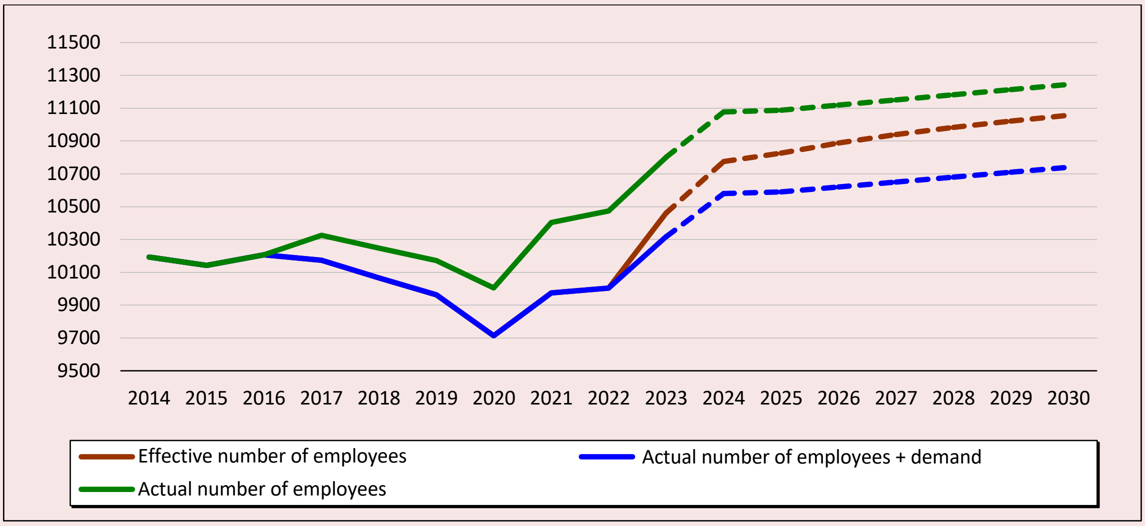
Based on the estimates of penetration and efficiency of generative AI use by industries, we can assess the effective number of employees L^* in each of the industries. There arises the possibility of using scenario approach and parametric modeling, when we can estimate the expected value of output by industries in the described system on the basis of the effective number of employees or, on the contrary, estimate the necessary number of employees that can provide the planned level of output taking into account the assumptions about the level of technology penetration, etc.

As we have mentioned above, it is necessary to take into account the needs V in addition to taking into account the number of employed L, then for each industry we can plot the dynamics of the values of the actual number of employed L, the effective number of employed L^* and the sum of the actual number of employed and needs $L + V$.

It becomes possible to use scenario approach and parametric modeling, when in the described system, we can estimate the necessary level of technology penetration to obtain a certain specified effect or, on the contrary, estimate the possible effect taking into account assumptions about the level of technology penetration, etc.

The calculations have shown that generative AI can reduce the existing staffing hunger in some areas and its impact will not exceed the current staffing needs. *Figures 5, 6* show an example of the dynamics of the number of the employed and the dynamics of the need in personnel on the example of the industry (C) "Manufacturing industries".

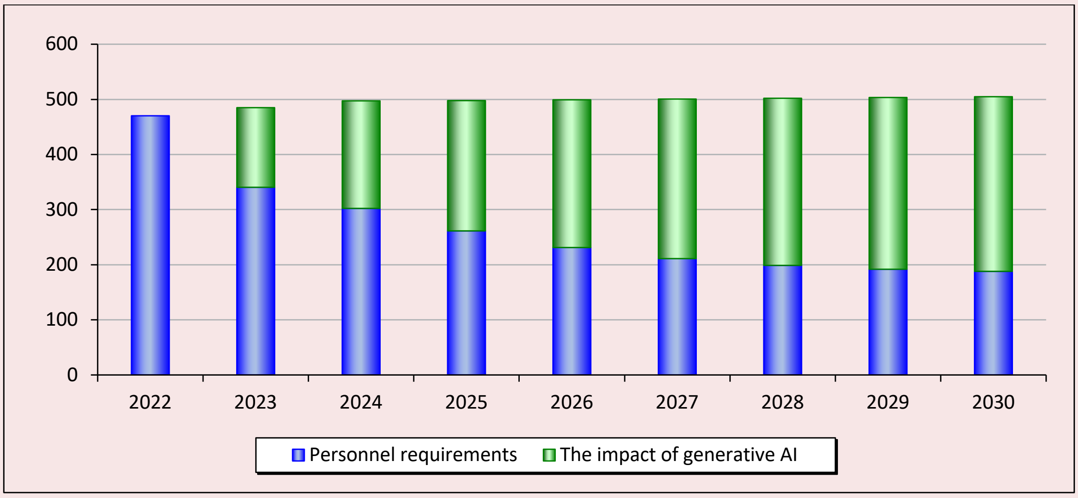
Figure 5. Dynamics of the number of employed for industry (C) "Manufacturing industries", thousand people



[5] The Economic Potential of Generative AI. McKinsey Report, January 2023.

[6] Turning GenAI Magic into Business Impact. Available at: https://www.bcg.com/publications/2023/maximizingthe-potential-of-generative-ai (accessed: February 16, 2024); Goldman Sachs: Upgrading Our Longer-Run Global Growth Forecasts to Reflect the Impact of Generative AI (Briggs/Kodnani); The Economic Potential of Generative AI. McKinsey Report, January 2023.

Figure 6. Dynamics of demand for personnel in branch (C) "Manufacturing industries", thousand people



The example of forecasting the dynamics of the number of the employed and the dynamics of the need in personnel for the industry (K) "Financial and Insurance Activities" (*Fig. 7, 8*) shows how in a number of industries the impact of generative AI can exceed the existing needs in personnel (wholesale and retail trade; repair of motor vehicles and motorcycles; information and communication activities; financial and insurance activities; professional, scientific and technical activities; education; activities in the field of culture, sports, leisure and entertainment). Excess of the effective number of employed persons over the needs may lead to the growth of industry output above the forecast values or to a decrease in the actual number of employed persons in certain industries.

Figure 7. Dynamics of the number of employed for industry (K) "Financial and insurance activities", thousand people

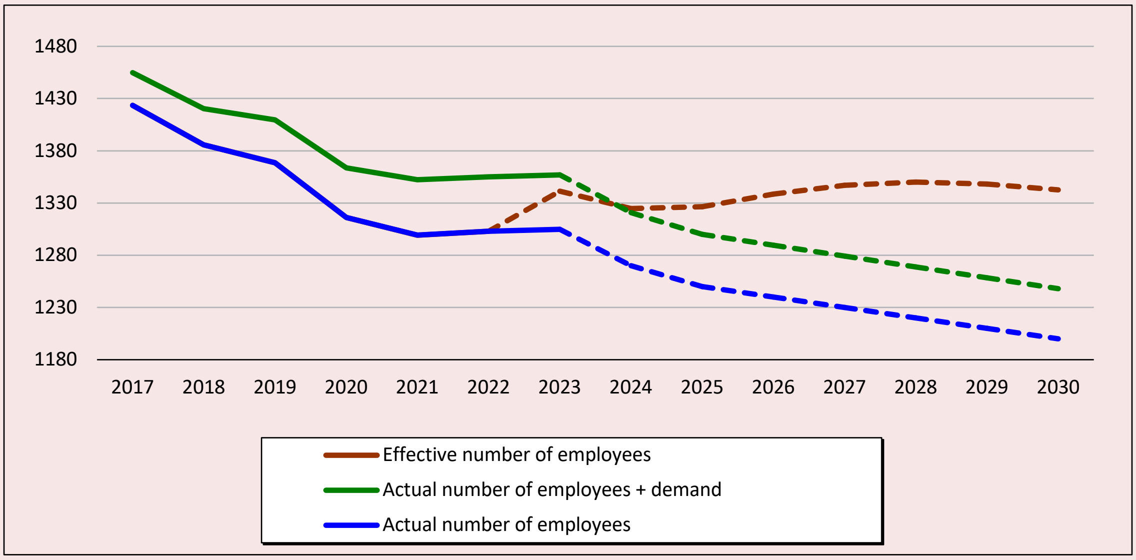


Figure 8. Dynamics of aggregate data on the number of employed by sectors (A-S), thousand people

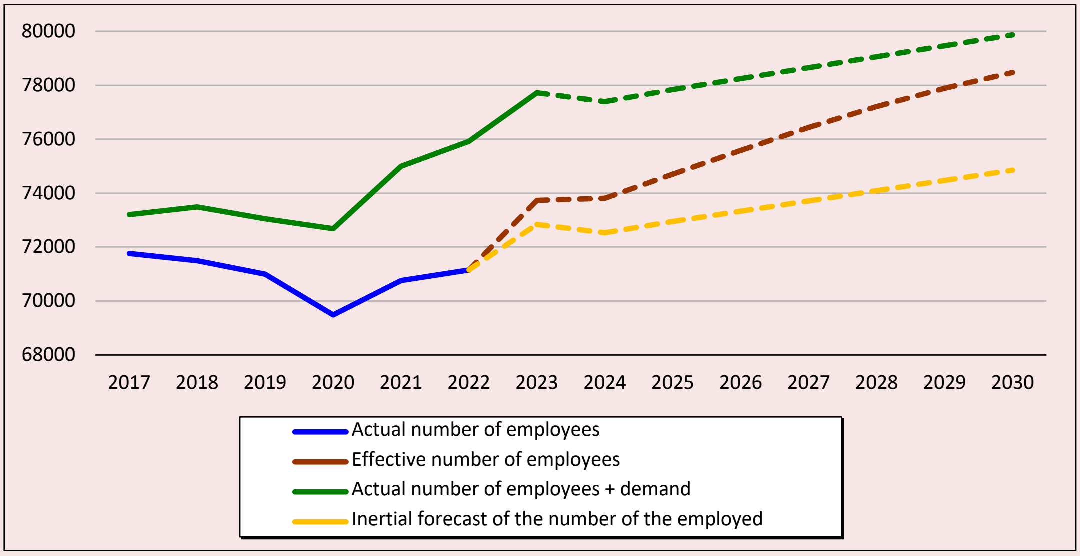
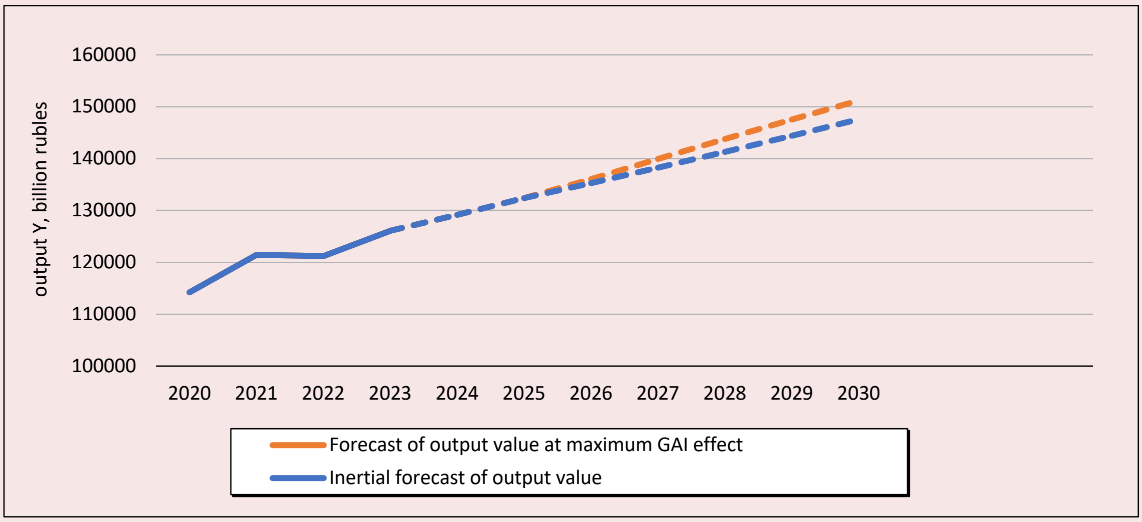


Figure 9 presents the total impact of generative AI on the labor market. We can see that taking into account the impact of generative AI, according to the estimates of the degree of technology penetration in industries and estimates of technology efficiency, we can expect that the existing shortage of personnel can be leveled by about 80%, while we can expect output growth (the sum of GVA by A-S industries) by 2.5% by 2030. This scenario implies that the number of the employed will be in line with the inertial forecast, and output growth is ensured by an increase in the effective number of employed persons. There is a scenario when the increase in labor efficiency will not only cover the needs of a particular industry, but will also lead to the release of some of the employed, to their transfer to other

Figure 9. Scenarios of output growth (sum of GVA by A-S industries) taking into account generative AI, billion rubles



industries where the need for personnel is expected to remain. The graphs of the inertial forecast and the forecast of output values taking into account the influence of generative AI form a superposition of scenarios, i.e. a certain area of possible values.

Conclusion

In conclusion, we should note that the generative AI impact on the labor market is a topical issue. The calculations are based on Rosstat data, forecasts by the Ministry of Economic Development of the RF and the Ministry of Labor of the RF, and estimates by McKinsey, BCG and other analytical agencies. They confirm that the introduction of generative AI is a powerful driver not only for productivity improvement, but also for a major structural change in the labor market. The modified Cobb – Douglas function used in the study showed that in a number of industries, the impact of technology can significantly change the balance of jobs, especially in industries where technology penetration and labor efficiency growth are estimated to be higher (wholesale and retail trade; repair of motor vehicles and motorcycles; information and communication activities; financial and insurance activities; professional, scientific and technical activities; education; cultural activities; cultural and technical activities; and social activities). In total, these sectors form more than 25% of GDP.

One of the key findings of the study is the need to manage the effects of technology adoption, which could close 80% of the current job gap. The adaptive capacity of markets will depend on how quickly government and companies can integrate new technologies into the economy. Forecasts show that if generative AI is applied on a mass scale, the technology will not only offset the labor shortage, but also provide an overall GDP growth of 2.5%. The graphs of the inertial forecast and the forecast of output values taking into account the impact of generative AI form a superposition of scenarios, i.e. a certain area of possible values. Such results confirm the need for a comprehensive approach, which should include retraining programs and active introduction of new technologies in all sectors of the economy.

Thus, in our study generative AI is considered not as a tool for replacing human labor, but as a tool for increasing labor efficiency (productivity). Generative AI at the existing level of technology development allows saving up to 15–25% of employees' time on routine tasks related to processing and analyzing text information. The share of employees performing such work in various industries reaches 10, 30 and 50% depending on the specifics of the industry, which is a potential for the application of generative AI in the economy.

The proposed approach is a primary assessment of the impact of generative AI technology on the labor market, which, of course, cannot take into account all possible structural changes in the economy. Possible changes in the balance are so significant that they change the points of economic equilibrium and many feedbacks, which will have to be taken into account in the future, but the proposed method of assessing the impact of technology can be their basis, it is stable in relation to changes in expert assessments of the initial parameters of the model and gives an initial estimate of the transformation of employment in sectors of the economy, onwhich we can base further research.

It seems promising the analysis of labor market changes under the influence of generative AI in the context of professions. The task of modeling the processes of changing the balance of labor resources in terms of not only employment by industries, but also by occupations arises, since, apparently, it can be assumed that there will be transitions of people not only from industry to industry, but also within industries, and transitions from industry to industry may be accompanied by a change of occupation.

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