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Financial and Economic Consequences of Distribution of Artificial Intelligence as a General-Purpose Technology

V.E. Rasskazov
Rostelecom PJSC, Moscow, Russia
https://orcid.org/0000-0001-5593-2591

ABSTRACT

The **relevance** of the article is due to increasing attention of the state and corporations to artificial intelligence technologies, developing strategies and increasing investments in technology. **The aim** of this article is to study artificial intelligence as a general-purpose technology, its distribution features and approaches to assessing and modelling the impact on production, organization finances and the economy. The study employed the **methods** of an AI qualitative analysis according to the classification of general-purpose technologies and a regression analysis of company production factors. The author analysed the data of 21 public Russian companies in the industry of hydrocarbon production, mining and metal production for 2014–2018. He proposed a model to assess the impact of AI technology on production, organization finances and the economy. The correlation analysis proved that capital expenditures and the market value of companies have a close relationship. The study revealed low productivity of assets of Russian companies. The investor expects to receive 28 kopecks for each rouble invested in the company's assets, whereas foreign markets show a one to one ratio. The study highlighted the cyclicality of the performance of the company factors. The research did not expose general-purpose technology signals in the given time interval. The author **concluded** that under a quality classification, artificial intelligence is a general-purpose technology; however, at this stage, it is impossible to empirically observe the economic effect of the technology distribution. The proposed model may be of further use to study the effect of artificial intelligence on the finances of a company and the economy. The potential consequences of market monopolization due to the distribution of AI technologies allow for an argument for the state regulation of the technology adaptation process by business.

Keywords: general-purpose technology; Artificial Intelligence; Solow's paradox; J-curve; analysis of production factors; financial and economic analysis

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INTRODUCTION

General-purpose technologies (GPTs) are a class of technological innovations, characterized by pervasiveness, innovation spawning and high potential for subsequent improvements. Steam engine, electricity, internal combustion engine, computers and biotechnology — each of these technologies once became a catalyst for complementary innovations and economic development of humanity, and thus, a general-purpose technology. Such technologies allow numerous improvements and use cases that contribute to increasing the return on production factors. It is no coincidence that GPTs are considered one of the most important engines of growth of society [1].

At the same time, GPTs are extremely rare. According to Richard Lipsey and Kenneth Carlow, only 24 technologies in the human history fall under this classification [2]. The researchers used the following classification criteria:

- the technology is based on a general multipurpose principle;
- initially, the functionality was limited, but as technology develops, it becomes widespread in the economy due to lower cost of use;
- the technology contributes to many related innovations.

Available estimates have shown that the pervasive IT revolution supported 0.60% of labour productivity annual growth between 1995 and 2005 and the use of robots within manufacturing raised the annual growth of labour productivity by 0.36% between 1993 and 2007 [3]. The economic effect of the spread of a particular technology may seem insignificant, but the cumulative effect of the spread of several GPTs reaches 2.0–2.5% of the annual labour productivity growth [4]. In the long run, this doubles labour productivity every 30–35 years. For comparison, in the period XIII — XVIII centuries the annual labour productivity growth in the Netherlands was only 0.2% [5].

Among the emerging technologies, the most likely GPT is artificial intelligence (AI). Unlike other innovations, united by the concept of "digital economy", such as the Internet of things, virtual reality, quantum computing and distributed ledger technologies, only AI meets the criteria proposed by R. Lipsey. The others either do not have a general principle, or are limited in development and application, or do not contribute to the development of related innovations[1].

Optimistic researchers believe that the development and spread of AI may lead to the fastest paradigm shift in technology history [6]. It is almost impossible to imagine a process or hardware where AI could not be applied. The possibilities of using AI are many times greater than the automation potential discovered with the spread of IT in the 1980s.

The study object is the impact of AI technologies on social development. The subject of this work is the study of the consequences of distribution of AI as a general-purpose technology. To achieve the aim of the study, it is necessary to perform the following tasks: to assess the innovative potential of AI, the features of similar GPTs, such as IT, as well as to trace the effect of the spread of AI in the economy.

INNOVATIVE POTENTIAL OF ARTIFICIAL INTELLIGENCE AS A GENERAL-PURPOSE TECHNOLOGY

Artificial intelligence is a general term that refers to hardware and software capable of intelligent behavior. The concept of "artificial intelligence" has existed since the 1950s, when AI referred to systems designed to simulate the work of experts. The AI algorithm operation is built on the optimization of some function based on a large number of observations. AI allows for the automated

[1] Will AI, Blockchain, AR and/or VR become a general-purpose technology? Hackernoon. Sept. 15, 2017. URL: https://hackernoon.com/ai-blockchain-ar-vr-etc-which-one-is-a-general-purpose-technology-9b5510ca25e3 (accessed on 02.04.2020).

solution of complex optimization problems when the developer has no information about data behavior and cannot set a linear data processing function.

AI innovative potential is to automate the search for a "data structure". Such functionality of a computer program makes large-scale automation of processes economically viable by reducing the cost of searching for missing information and making decisions. AI algorithms make it possible to calculate probabilistic outcomes or, in other words, "predictions" [7].

Classical linear algorithms used in IT are based on formalizing human-readable if-then logic. For example, if a person has reached the retirement age, then s/he will be rejected a credit. Usually, the system designer sets this logic of the program's work with data, and the utilization efficiency and the development of the algorithm depend directly on the conversion rate of knowledge about the business or process into machine-readable code.

It can be assumed that if management methods used by leading firms were used in the entire economy, it would be possible to empirically observe the declared productivity growth from GPTs.

In the case of AI algorithms, the developer does not write complete data processing logic, but only general rules — the design of the algorithm. Next, the algorithm searches for a suitable data structure necessary to optimize the function (*Fig. 1*). A model evolving from the observations is able to fill in the missing information — to predict. The predictions of the missing data supplement the incoming information about the new situation, so that the decision-making process can be fully or partially automated. Using the program's work result data allows the algorithm to develop considering the new information on the data structure.

AI performance depends directly on how well the cumulative data characterizes total situations that will employ the model obtained by the algorithm. Understanding this principle is important for a fair assessment of the AI utilization potential.

Despite the fact that only some AI researchers aim to imitate the human mind, historically, human intelligence is often used as a criterion for AI assessment. The human mind should not be the only criterion for comparing AI, since AI algorithms already perform some tasks much better than people do. Therefore, their performance should not be compared with people, but only with other AI solutions.

Artificial intelligence is capable to generate knowledge about the data structure much faster than humans are. At the same time, AI requires more observations than a person to learn how to navigate data. A computer is able to work without rest and with a more stable return than a person is. The program code can be infinitely replicated to many machines, which allows scaling the application of the AI algorithm with minimal costs. These features entitle to classify artificial intelligence as a GPT with more confidence.

Unlike the AI that exists today, a person knows how to work with data of high abstraction. Previous experience not related to the current task, and the ability to work with multimodal data (combining image, sound, semantics, etc.) [8] help a person effectively solve new unstructured problems. The other side of the human ability to use related experience is the danger of distorting perception, bias and using past attitudes to solve the current problem.

Perhaps in the future, a cross-functional, "wide", artificial intelligence will appear to program more abstract logic. However, the current AI technologies enable automating and optimizing such human abilities as perception,

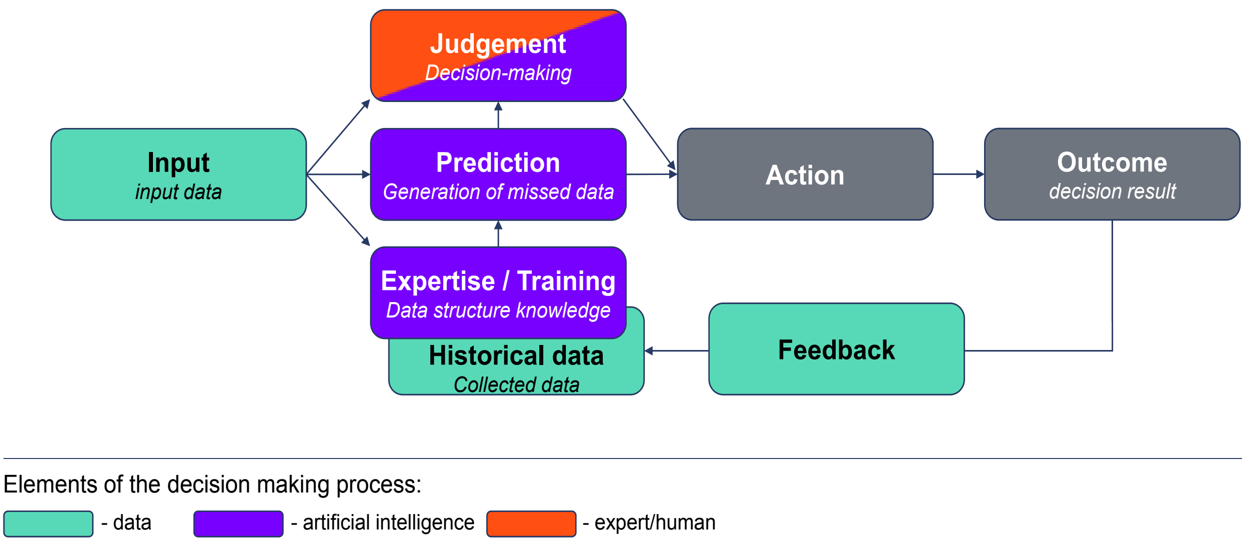

Fig. 1. **Artificial intelligence in decision making**

Source: compiled by the author.

understanding, reasoning, planning and communication, which makes it possible to use these abilities in a digital environment.

SOLOW'S PARADOX AND STIMULATING GPTS

Despite prior high expectations, it is difficult to evaluate the economic effect of AI utilization. If artificial intelligence is a GPT, the return on using the technology should be seen in the efficiency growth of production factors in each sector of the economy. Meanwhile, there is much empirical evidence that the so-called Solow's paradox often shows in relation to AI.

In the early period of total infatuation with computers, Nobel Prize winner Robert Solow [9] noted: "You can see the computer age everywhere but in the productivity statistics". The expected value of AI technologies often differs from objective indicators of business performance. The introduction of artificial intelligence in practice is often combined with production inefficiency.

There are three most popular approaches to Solow's paradox in the literature:

1. **Specific effect measurements**

The technology has a qualitative impact on people's lives, but the statistical tools used are not able to evaluate its impact in full [10].

2. **Uneven diffusion of innovations**

Slight gradual improvements are observed mainly in consumer technology. At the same time, the innovation diffusion in the economy is slowing down [11].

3. **Time lag between the appearance of innovation and its effect**

Potential for productivity growth already exists, but implementation methods and a deep understanding of innovation, important for the distribution of the technology in the economy, are not yet available.

While the first and the second explanations have not yet found empirical evidence, the theory of innovation diffusion barriers seems most likely. Many researchers support this explanation, since this approach helps remove the contradiction between the obvious long-term technological prospects of AI and low-key performance in the short term.

Every technological revolution caused by GPTs had leading companies capable of benefiting from innovations [12]. It takes time before other firms can learn to use GPTs and productivity growth will affect the economy as a whole. There are companies in various industries that lead in the adaptation of new technologies. These market leaders typically rely on less labour and more patents. Most of the AI developments are carried out in state research institutes and universities, while in IT-leading countries the entrepreneurial sector is the development driver of this direction [13].

It can be assumed that if management methods used by leading firms were used in the entire economy, it would be possible to empirically observe the declared productivity growth from GPTs. In this hypothetical scenario, the assessment of productivity growth from AI will not require new measurement tools, and the effect of technology diffusion will be no less significant than from the previous technological revolutions.

Sustaining the trend of concentrating AI utilization benefits among leading firms will result in market monopolization. This feature of innovation diffusion leads to redistributing market shares and creating market entry barriers for other participants. Therefore, to maximize public benefits and accelerate the growth of the national economy, the state should regulate the spread of GPT, including artificial intelligence technology. That is why more than twenty states have released AI strategies and programs for 2017–2018 at the national level [14].

The approaches of countries to describe the strategy are similar, and each strategy somehow highlights the following aspects of AI regulation:

- stimulation of scientific research;
- talent development, skills and education;
- public and private sector adoption;
- ethics and inclusion, standards and regulations;
- data and digital infrastructure.

The implementation of a national program following these principles should contribute to the democratization of technology.

IMPLEMENTATION AND DIFFUSION OF ARTIFICIAL INTELLIGENCE

Studying the influence of GPT on the company's productivity, the authors of the article "The productivity J-curve: How intangibles complement General Purpose Technologies" [15] drew attention to a systematic underestimation of output and productivity in the early years of investments in technological business development. Investments in intangibles, including AI, at the beginning of the investment cycle (the R&D and the beginning of implementation) do not create additional output, which means they underestimate the overall production productivity. In the long term, the accumulated innovative potential, on the contrary, leads to reassessing the growth of returns from production factors. This gives the performance dynamics a J-shape.

The J-curve effect is often cited in macroeconomics to explain the multidirectional effects on the trade balance of the devaluation of the national currency at different time periods [16]. In the case of a firm, this approach helps explain the temporary decrease in returns on production factors when making large-scale investments in innovations. The fact is that investments aimed at creating an intangible asset base harm sales promotion and capacity building. Therefore, in the short term, the productivity of the firm-innovator is estimated below the expected values. Since technological development of a company often leads to new types of capital and requires investment in intangible assets, the diffusion of a new GPT may lead to the J-curve at the firm or state level, as explained by Solow's paradox.

A key feature of the introduction and diffusion of artificial intelligence technologies is the need to set the algorithm specifically for each firm. Previous GPTs, such as computers, electricity, and internal combustion engines, spread linearly, as they were "product" GPTs. To solve the problem a GPT implementation it was enough to connect the engine to the working elements of the existing machine. With AI, it is a "process" GPT, which means a different procedure for introducing technology into the company activities. The start of AI utilization requires accumulating large data volumes characterizing the main business processes, which means that the moment of return on investment will be postponed.

The more the companies leading in the implementation of GPTs are ahead, the higher will be their productivity and the promise to reduce the cost of the final product. The process is clearly cumulative. Due to AI, the leading company will take a larger market share and make more transactions, which means it will accumulate more observations about production processes and will further improve AI.

The lagging firms, on the contrary, lose production volumes and slowly accumulate the data necessary for setting AI algorithms. Having lost the scale of production, these technologically weak market players can no longer automate internal processes due to AI. Anyway, the leader in the use of AI technologies creates barriers to market entry and losses for lagging firms.

Lack of regulation of AI technology diffusion may lead to monopolization of industries by leading firms. In some cases, monopolization is associated with an inefficient distribution of benefits from the GPT development; however, with moderate regulation, monopolization of industries can have a positive effect on the economy due to scale of production and capital accumulation [17].

The impact that monopolies have on society depends on their regulatory and social environment. If a monopoly is dominant due to effective investments in innovative product development, rather than artificially restraining competition by high marketing costs and price dumping, then the monopoly may stimulate progress and bring more benefits to society than the competitive market condition.

The evidence from practice shows [18] that post regulation of monopolies by the tools of antitrust law rarely takes effect, since it is extremely difficult to determine the level of competition necessary for the economy. The artificial restriction of market leading firms often leads to negative externalities.

The solution is to preventively regulate and support competition in the market. In terms of AI technologies, this could be stimulating research, developing human resources and creating a national information infrastructure[2]. Implementing the national strategy and program for AI development in Russia should contribute to the balanced diffusion and regulation of AI technologies in the Russian economy.

Russian literature is revealing the attitude to the diffusion and implementation of AI technologies. Artificial intelligence can help solve the problems of reducing the working-age population and modernizing obsolete production capacities [19]. Along with the productivity problem, there is an issue of proper stimulation and allocation of economic profit from AI as a new production factor [20].

The more the companies leading in the implementation of GPTs are ahead, the higher will be their productivity and the promise to reduce the cost of the final product.

The domestic literature puts forward a hypothesis that AI will transform the nature of human labour and will free the human resource for more complex and creative tasks [21]. Nevertheless, the ethical use of AI remains the problem. Its solution will require a phased transformation of the organizational structure through additional investments and the accumulation of new managerial experience in the field of artificial intelligence technologies [22], as well as the definition of AI as an object of legal relations [23].

[2] Almanac "Artificial Intelligence". Current state of the AI industry in Russia and the world. No. 1. M.: Center for Competence Research Institute on the basis of MIPT in the field of "Artificial Intelligence"; 2019. P. 153

APPROACH TO THE ANALYSIS OF GPT EFFECT

Assessing GPT effect often employs an approach based on factorial analysis. It is necessary to reveal the relationship between the company's total output and production factors. The company's net receipts at time t is as follows [24]:

$$Y = p * F(K, N, I, A). \qquad (1)$$

where Y is the company's net receipts; p is the price of goods; K is the vector of capital goods (assets) with price r; N is the vector of variable costs (operating expenses) with price w; I is investments with a price z; A denotes the total productivity of production factors.

The present value of a firm can be expressed as the total cash flows to the date.

$$V_0 = \int_0^{\infty} \left[p * F(K, N, I, A) - w'N - z'I \right] * u(t)\, dt, \qquad (2)$$

where $u(t)$ denotes cumulative discount factor.

According to the transformations described in work [15], the equation for a firm valuation can be as follows

$$V_0 = \sum_{j=1}^{J} \lambda_{j,0} * K_{j,0}, \qquad (3)$$

where λ is the coefficient adjusting the value of production assets (K), and j is the index of different types of capital used in production. The use of coefficient λ characterizes the adjusting costs of production assets. For a company investing in intangible assets and improving performance, the λ/z indicator (ratio of the premium rate to the cost of investment) is expected to be more than one.

By showing the dependence of value of companies on production factors, i.e. assets (total assets, TA), operating expenses (sales, general and administrative costs, SG&A) and expenses on innovation (research and development, R&D), it is possible to assess the effect of each production factor on the company's value

$$\begin{aligned} Market\,Value = \alpha + \beta_1 TA + \\ + \beta_2 SG\,\&\,A + \beta_3 R\,\&\,D + \varepsilon. \end{aligned} \qquad (4)$$

For an empirical performance assessment of the production factors, coefficients β for companies of various sizes and industries can be considered. This approach should help assess the effect of investment in innovation on production factors.

Further decomposition of production factors to determine the element characterizing the accumulation of data may help find a connection between the payback period of investments in process automation and the size of the company. Identifying this pattern is useful to find the optimal investment strategy in AI technology, as well as to find the necessary measures for state regulation of the new GPT.

EXPERIMENT

The experiment used the data from Russian public companies in the hydrocarbon, mining and metal industries. Collecting data to assess the effect of industry production factors is a laborious process, so the number of companies in the sample was limited to 21 and the time period 2014–2018 (*Table 1*). The focus on mining industries is justified by a similar operating model for these companies. Adding the financial serves, engineering, or trading sectors to the common database could create noise in obsving the accumulation effect of technological base.

Unlike foreign companies, Russian business does not consider or declare R&D expenses. For the purposes of the study, this is a complication, since it was assumed that investments in new technologies would be described precisely by investments in R&D. As a possible workaround, in addition to the factors described above, the study assesses the impact of annual capital investments.

Table 1

List of companies in the sample

Oil and gas		Metals and mining	
Gazprom	Tatneft	Evraz	Mechel
LUKOIL	NOVATEK	NLMK	ALROSA
Rosneft	Slavneft	Rusal	TMK
Surgutneftegas	Russneft	Nornickel	Polyus
Transneft		Severstal	ChelPipe
		MMK	Polymetal

Source: compiled by the author.

Table 2

Correlation of database parameters

	MV	TA	COGS	SG&A	other OPEX	total OPEX	CAPEX
MV	1						
TA	0.65	1					
(COGS)	0.80	0.76	1				
(SG&A)	0.61	0.58	0.82	1			
(other OPEX)	0.77	0.46	0.76	0.59	1		
total OPEX	0.84	0.70	0.97	0.81	0.88	1	
CAPEX		0.92	0.85	0.64	0.70	0.84	1

Source: compiled by the author.

To create the model, we compiled a database of annual reporting indicators for companies including such parameters as: market value of paper at the end of the year (market value, MV), assets (total assets, TA), production cost (costs of goods sold, COGS), sales costs (sales, general and administrative costs, SG&A), other operating expenses (other OPEX), total operating expenses (total OPEX) and capital expenses for the period (CAPEX).

The correlation analysis of parameters show that the capital expenses (CAPEX) and market value (MV) of the company have a close direct relationship (*Table 2*). This relationship validates the inclusion of CAPEX in the model. In the case of operating expenses, the inclusion of cost does not make economic sense; and other operating expenses are calculated by companies in different ways. Therefore, the model will deploy the synthetic parameter "operating expenses minus production costs".

In the regression model, beta coefficients were calculated for each individual period with the point of intersection of axis at zero. It is interesting that if the intersection point of the OY axis is not fixed, one can see a change in the axis intersection point for the period 2014 to 2018 by + 131%. This is close to the growth of the price index for the respective industries, + 122%, which means that the sample describes the market quite well.

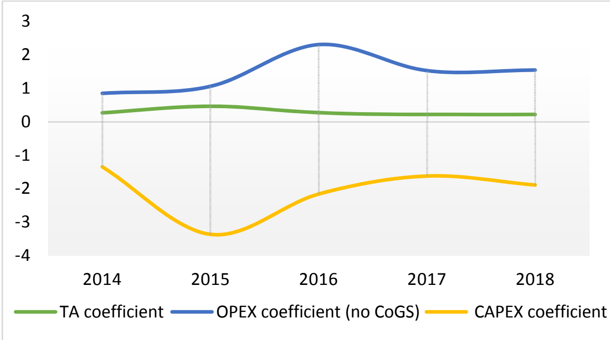

Fig. 2. **Beta model regression coefficients by production factors**

Source: compiled by the author.

The obtained values of production factors correspond to foreign studies. *Fig. 2*, presumably, presents two effects specific to the Russian market and the selected time period — low asset performance and the investment cycle of the technological base update.

An important difference between the obtained data from the results in foreign studies (*Fig. 3*) is in the low asset performance. If for the American market the value close to one is economically sound, then the graph shows the asset performance ratio close to 0.28 (*Table 3*). The investor expects to receive 28 kopecks for each rouble invested in the compa-

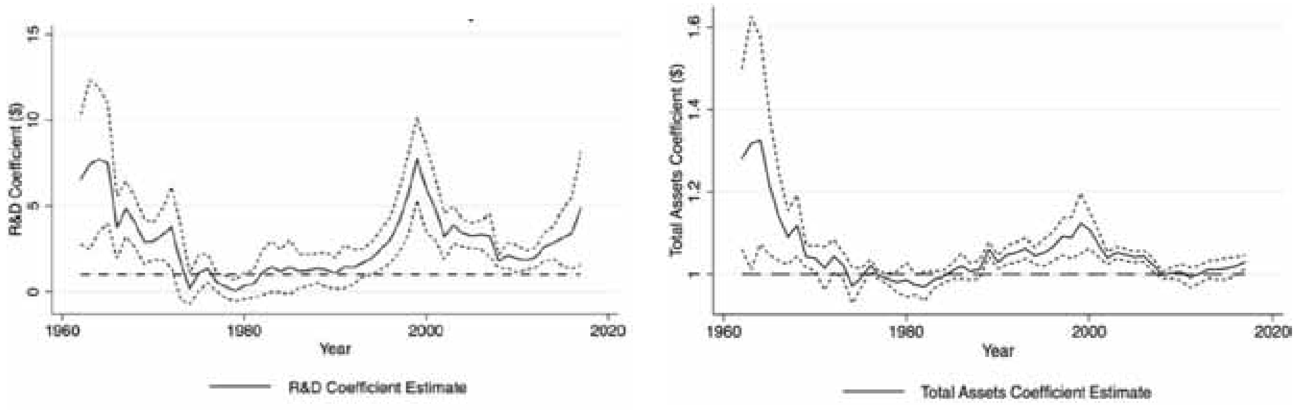

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Fig. 3. **Beta ratios for assets and R&D**

Source: study by Brynjolfsson E. et al.[15, p. 24, 25]. URL: https://economics.stanford.edu/sites/g/files/sbiybj9386/f/brynrocksyv_j-curve_final.pdf (accessed on 02.02.2020).

Table 3

Average value of the coefficients and their change

	β average value	CAGR, 2014–2018, %
TA coefficient	0.28	–5
OPEX coefficient (no CoGS)	1.46	16
CAPEX coefficient	–2.08	9

Source: compiled by the author.

Table 4

OPEX and CAPEX costs to assets, %

	2014	2015	2016	2017	2018	CAGR
OPEX/TA	11.8	10.6	14.8	17.0	20.0	14.2
CAPEX/TA	7.1	8.9	8.9	9.4	8.8	5.5

Source: compiled by the author.

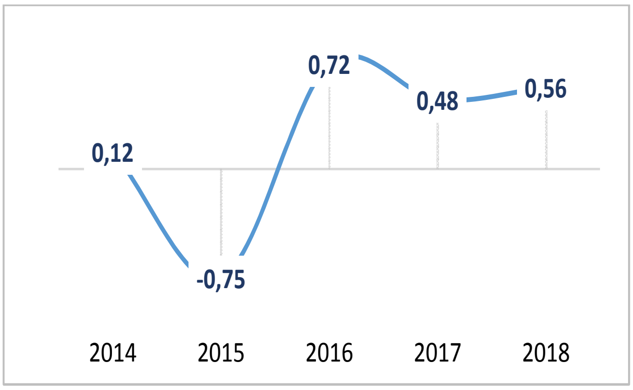

Fig. 4. **Beta model regression coefficients by production factors**

Source: compiled by the author.

ny's assets, whereas foreign markets show a one to one ratio. Such a low return on assets also explains the negative CAPEX coefficient, as investors consider investments in the company's capital as an inefficient management of funds that reduces the company's valuation.

The low asset performance may be explained by a high level of debt of companies, a high government share in business and a negative macroeconomic background.

Fig. 2 shows the progress of the investment cycle, due to which the OPEX performance is growing. A new, more advanced asset base allows companies to mine large volumes of resources with less labour and variable costs. The intensity of the use of assets is also growing (*Table 4*), which is seen in the growth of operating expenses relative to the volume of assets.

$$\Delta\, effect = \sum_{i=1}^{n} \beta_{OPEX} * OPEX_i + \\ + (\beta_{CAPEX} + \beta_{TA}) * CAPEX_i. \quad (5)$$

In conclusion, we can assess the cumulative effect of changes in the production factors performance over the observed period (*Fig. 4*). In the period 2014–2018, one can observe the progress of the cycle. We cannot be sure whether it was an investment cycle or a change in market conditions, justified by the influence of macroeconomic factors.

The cycle resulted in the increased OPEX performance by 40%. The mere technological base update is unlikely to produce this result, so the impact of macroeconomic factors is plausible. Nevertheless, since asset performance has remained virtually unchanged, we may speak about the transition of the industry to a more efficient and technologically advanced operating model.

The study results allow for the conclusion that it is hardly possible to single out the effect of investments in new technologies, and even more so artificial intelligence, by observing fundamental and market indicators.

We noticed the general trend and cyclical development of the market, but it is easy to relate them to individual production factors, such as increasing the technological base or investments in the creation of new technologies.

CONCLUSIONS

The article provides arguments regarding the role of artificial intelligence in improving the efficiency of business and national economies as a "process" general-purpose technology. The paper also provided arguments for the investment in automation of production with AI technologies: increasing the return on production factors and creating sustainable competitive advantages by increasing barriers to entry into the industry.

The low asset performance may be explained by a high level of debt of companies, a high government share in business and a negative macroeconomic background.

The experiment made it possible to find the cyclical development of the market, which can be associated with the transition of companies to an improved and more technologically advanced operating model. However, we failed to identify a causal relationship between investments in new technologies and increased returns on the company's production factors due to a lack of necessary data in the official statements of the companies. Thus, the analysis of fundamental and market indicators of companies does not provide effective indicators for investment decisions regarding the development of the technological base of the company, or investments in AI technologies. The main reason for this conclusion is the lack of open data sufficient to conduct a focal study. Available indicators are not indicative since their value is affected by many factors.

The management may be skeptical about investment decisions on the development of AI technologies due to the short-term planning horizon and the specifics of motivation. Implementing a business development strategy with artificial intelligence is within the range of 5–10 years, which goes beyond the KPI of investment decision-makers. Moreover, investments in new technologies have a negative impact on the company's performance while accumulating production potential. Therefore, decisions on investments in AI will be made mainly by business owners, and in the case of many Russian enterprises — by the government.

Studies on the patterns of the GPT diffusion in the economy support moderate government intervention in the development of AI technologies. As is the case with the Internet or semiconductors, financing research and developing infrastructure will take a long time before there appear market motivators for adaptation and further development of GPTs.

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ABOUT THE AUTHOR

Vladislav E. Rasskazov — Program Manager, Business development department, Rostelecom PJSC, Moscow, Russia
rasskazov.vladislav@gmail.com

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