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REGIONAL DETERMINANTS OF EFFECTIVE USE OF HUMAN CAPITAL IN THE DIGITAL ECONOMY

This article discusses peculiarities of the labour market functioning in the context of the digital economy development. It determines the main directions in the management of processes related to the accumulation and use of human capital as the production's main factor in the context of digitalization. Our goal was to develop a multi-factor model of human capital efficiency in the digital economy. We used the materials of the Boston Consulting Group, the World Development Bank, and data from The Russia Longitudinal Monitoring Survey — Higher School of Economics (RLMS-HSE) as the study's empirical base. As a research methodology, we chose a regression analysis based on the initial sample of data from RLMS 25, wave 2016, "Data on IBM SPSS individuals". For the study of factors, we utilized the traditional J. Mincer equation, supplemented by quantitative and qualitative variables. We proved that expanding the range of parameters increases the coefficient of determination and the statistical significance of the parameters. On the basis of the empirical material, we confirmed a number of hypotheses on the determinants of the effective use of human capital in the digital economy. Particularly, the hypothesis about the impact of production experience on wages as an indicator of returns to human capital, previously put forward and supported by J. Mincer and his followers, is not confirmed for the digital economy. Digital technologies, replacing the old working methods, render the previous skills and organizational approaches irrelevant. Transformations caused by the environment's automation and digitalization change the working activities from clearly defined work responsibilities to design work. The development of skills in digital knowledge application is an essential factor for the effective use of human capital in the digital economy. These skills enable workers' adaptation to changing work processes and the employers' requirements. The study's results show that the correct interpretation of the determinants that affect the efficiency of the human capital use allow choosing the right targeting tools for managing human capital as a factor of economic growth.

Keywords: human capital, intellectual economy, wages, Mincer equation, regions of Russia, education, special competences, modelling, regression analysis, indicators, statistics

Introduction

The development of the digital economy has led to qualitative changes in the management of human capital. These fundamental changes in the last decade became the focus of theoretical and practical research, which led to the formation of a new socio-economic paradigm [1, p. 214; 2, p. 125; 3, 145; 4, p. 95].

Over the past few years, the economy's diversification and adoption of the digital development trajectory have been taking place. Their fundamental prerequisites are the domination of global technological, demographic and geopolitical trends that undermine the existing division of labour processes and shape the predominance of the artificial intellectualisation in the labour market. The workers who are able to work in the uncertain environment and perform complex analytical tasks play the significant r ole in this market, as they have the core universal competences without which it is impossible to come to an efficient digital economy.

We are entering the era of mass digitalization, which covers all sectors of the economy and changes ways of living and working. Humanity will be immersed in data and globally connected by means of mobile technology environments, smart homes and smart cities, drones, street robotics, the Internet of things. Technological trends will have the greatest influence on business processes and relevance of the digital skills in work now and in the near future. The widespread use of the digital technologies, artificial intelligence, robotics, virtual reality and other innovations have a powerful impact on the formation and development of human capital.

In 1995, the American scientist Nicholas Negroponte from the University of Massachusetts introduced the term "digital economy". In 2016, one of the key papers of the World Bank called "Digital Divide" has presented the content of the report on the state of the world's digital economy. R. Meshcheryakov offers two approaches to the term "digital economy". Firstly, in the context of the

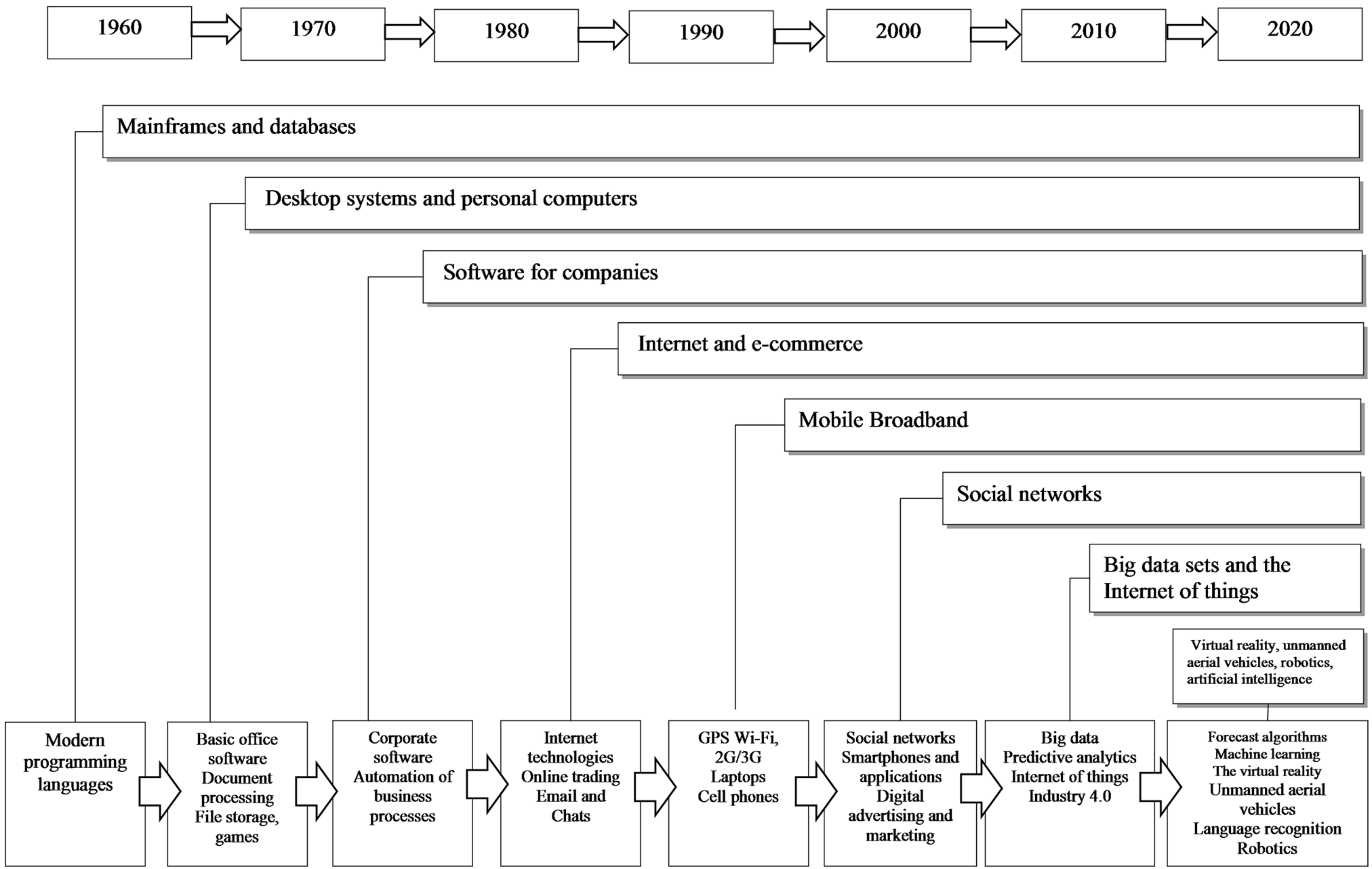

Fig. 1. *Stages of development of the digital economy (comp. by the authors based on [2, p. 4; 5; 24])*

classical approach, the digital economy is understood as an economy based on digital technology. In this case, the term is mainly characterized by the sphere of electronic services and goods (telemedicine, distance learning, the sale of media, such as movies, television, books, etc. are the classic examples). Secondly, in the context of a more advanced approach, the digital economy refers to the production using indicators such as Internet technology, "Industry 4.0" technology, "Smart factory", as well as the use of the fifth-generation communication networks, prototyping engineering services, etc.

Influenced by the increasing role of information and knowledge in the business environment, the need to manage the processes associated with the accumulation and use of human capital as a carrier of this knowledge became urgent. In this regard, we propose the author's approach to the term "digital economy", in which the predominant role is given to information and knowledge as important production resources, as well as to the active use of digital technologies for storing, processing and transmitting the information and knowledge. Information and knowledge become valuable and the most relevant factors of production.

Since the middle of 1970s, there has been an acceleration of changes in the technological environment, which we can easily see in the frequency of the major innovations in Information and Communication Technologies (ICT) (Figure1).

The growing complexity of the environment and acceleration of technological changes cause the appearance of new forms of social interaction. Such changes affect both organizations and the society as a whole. Due to the pressure of rapid technological changes, the environment's complexity and uncertainty, society is moving towards blurring the boundaries between communities, generations of people, between work and personal life. Technological progress, the network society's development (about 87 % of the countries belonging to the Organisation for Economic Co-operation and Development (OECD) are already connected to the global network) and the spread of blockchain-based solutions shape a network society, which manifests itself in the people's changing attitude towards work, consumption, leisure and other aspects of life. This will affect the social institutions' ways of functioning and forms as they develop, and, hence, the demands of the workers employed in these institutions. In the near future, the following technological trends will have the greatest impact: the development of the mobile Internet, the Internet of things, artificial intelligence, big data and machine learning, VR/AR-technology, automation and robotics in industry and economy. The accelerating process of transformation of the economy's classical branches has become irreversible.

The digital economy is transforming the social paradigm of people's lives and business processes, in which priorities are set towards reducing the importance of the tangible asset and increasing the value of the knowledge and digital asset as the basic source of income. In the developing digital economy, information, knowledge and digital technologies are the main production factors.

Main part

The processes associated with the accumulation and use of human capital, as well as with the measurement and assessment of the effectiveness of investments in human capital, are actively studied in the social, humanitarian and economic spheres. At the same time, the assessment of its economic importance for more than 60 years remains unchanged and is not subjected to significant transformations in the works of both foreign and Russian scientists [4, p. 25; 5, p. 168; 6, p. 25; 7, p. 45; 8, p. 166; 9, p. 854; 10, p. 76; 11, p. 45; 12, p. 26; 13, p. 4; 14, p. 105; 15, p. 191; 16, p. 77; 17, p. p. 125]. The unity of numerous opinions is manifested in the definition of human capital: human capital is a special form of capital, including knowledge, skills, generating income for its carriers for a certain period and effectively used in the labour market [18, p. 98; 19, p. 45; 20, p. 77]. Theoretical and methodological views on the nature of human capital in the works of representatives of the neoclassical labour economy suggest its temporary dimension: the effectiveness of investment in human capital is determined by the difference in earnings among workers with different levels of the accumulated human capital [21, p. 58; 22, p. 108; 23, p. 46; 24, p. 198; 25, p. 48]. In modern studies, the definition of the efficiency of human capital is linked to the identification of its value's qualitative indicators. At the same time, monetary assessment cannot give the right idea of the impact of both quantitative and qualitative factors on the efficiency of the human capital use; in addition, the digital economy requires new qualitative determinants during the process of human capital formation. In this regard, the monetary assessment of human capital should be supplemented by studies of the multi-parameter influence of other factors on the resulting indicator. For this purpose, we use the traditional

Table 1

Data on the number of sample observations and their validity by region for 2016

№	The subject of the Russian Federation	The number of observations	The proportion of observations of the total,%
1	Amur oblast	246	2,6
2	Astrakhan oblast	387	4,1
3	Belgorod oblast	456	4,8
4	Bryansk oblast	438	4,7
5	Vladimir oblast	456	4,8
6	Volgograd oblast	157	1,6
7	Voronezh oblast	397	4,2
8	Ivanovo oblast	245	2,6
9	Irkutsk oblast	438	4,7
10	Kaliningrad oblast	136	1,4
11	Kemerovo oblast	327	3,5
12	Kirov oblast	327	3,5
13	Leningrad oblast	385	4,1
14	Lipetsk oblast	286	3,0
15	Magadan Oblast	157	1,6
16	Moscow oblast	358	3,8
17	Novgorod oblast	374	4,0
18	Oryol Oblast	358	3,8
19	Penza oblast	256	6,5
20	Rostov oblast	136	1,4
21	Saratov oblast	396	4,2
22	Sverdlovsk oblast	412	4,4
23	Tyumen oblast	558	3,8
24	Tula oblast	146	1,6
25	Yaroslavl oblast	260	2,7
26	Moscow	358	3,8
27	St. Petersburg	385	4,1
28	Khanty-Mansi Autonomous Okrug — Ugra	325	3,4
29	Yamalo-Nenets Autonomous Okrug	369	3,9
	Total	9318	100

methodology of econometric modelling based on the regression equations to study the processes of the human capital's formation and development.

Research methodology

The initial sample for in-depth analysis of the presented data from the Russian Longitudinal Monitoring Survey (RLMS) wave 25, 2016 "Data on individuals IBM SPSS" [1] . The RLMS sample included data from 9318 respondents from 29 regions, as well as 863 variables on the social and economic situation of individuals, their level of education, employment, qualification, professional and industry affiliation, health, etc. The data of the study by regions, the sample set and the validity assessment are presented in Table 1.

The traditional tool in the study of factors "affecting the level of return on education'' is the Mincer's equation [12, p. 12; 13, p. 2] that is a function of the logarithm of wages depending on several parameters. It includes the following variables:

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[1] Russian monitoring of the economic situation and public health of the Higher School of Economics. Survey data in SPSS format. Retrieved from: http: //www.hse.ru/rlms/spss. (Date of access: 20.05.2017).

$$\ln W = \beta_0 + \beta_1 N + \beta_2 X + \beta_3 X_2 + K, \quad (1)$$

where W is the value of wages, monetary units; β_0; β_1; β_2; β_3—coefficients of the regression equation; N—the number of accumulated years of education, years; X—production experience, years; K—the influence of factors not included in the model.

There are other modifications of this equation, which depend on the purpose of the analysis and may include an indicator of the unemployment level, population's employment, etc. So, R.J. Willis notes that the coefficient β_1 of the equation (1), which he calls the coefficient of education, reflects the rate of return on education and illustrates the increase in the return on each additional year of education [17, p. 125]. When using the standard Mincer model for analysis, the results are limited to this range of parameters, so modern researchers modify the equation (1), adding quantitative and qualitative variables [8]. Expanding the range of parameters, the coefficient of determination and statistical significance of the parameters increase. For in-depth analysis, we have proposed a linear model:

$$\ln W = x_0 + x_1 Y + x_2 L + z_1 E + z_2 G_e + z_3 B_o + \sum_{i=1}^{n} z_i R_{ei} + \sum_{j=1}^{k} z_j P_{nj}, \quad (2)$$

where x_i are the coefficients of the quantitative determinants; z—coefficients of the quality determinants; Y—age determinant, years; L—determinants of production experience; E—education; G_e—gender; B_o—profession; R_e—region; n—number of the regions in the study, $n = 29$; P_n—industry, $k = 16$.

The second model contains only qualitative determinants:

$$\ln W = \psi_0 + \sum_{a=1}^{b} \psi_{1a} Q_{Fa} + \sum_{c=1}^{d} \psi_{2c} S_{Lc} + \sum_{e=1}^{g} \psi_{3e} S_{spe} + \sum_{h=1}^{l} \psi_{4h} SO_h + \sum_{f=1}^{z} \psi_{5f} H_{ef}, \quad (3)$$

where ψ is the regression coefficients; Q_F—the level of the employee's competence; b—the number of qualification levels, $b = 8$; S_L—level of education; d—number of levels of professional education, $g = 2$; S_{sp}—target competence; g—number of target competencies, $d = 3$; SO—indicator of social status, $i = 2$; H_e—number of sickness absence days, reflecting health capital, $z = 3$.

Assessment of the coefficients in these models given below will be the basis for the study of human capital development trends in various regions of Russia.

The results of the regression analysis for the initial sample are presented in Table 2.

In the context of digital economy, professional skills alone are not enough. Clearly, this will lead to an imbalance of competence in the labour market; workers who have not been retrained may no longer be in demand in their specialty in 10 years. Today, the presence of only professional skills is already insufficient. Assimilation of the competences such as foreign language proficiency "Foreign Language Skills", the skills of working with large digital data work BigDate Skills, using digital technology "Digital Skills" is important in the digital economy.

The emphasis has changed to the development of composite integrated skills of cooperation and communication in the digital environment as opposed to narrowly understood computer literacy. It is important to consider digital skills, which encompass technical knowledge in ICT, in close relation to soft skills and general knowledge. For example, this approach vividly illustrates the "Target Competence Model 2025" prepared by BCG based on the consensus opinion of experts and analysis of the approaches of the Lominger Competence Library, Sberbank, RosExpert / Korn Ferry, HSE, WorldSkills Russia and Global Education Futures. This model, in addition to the purely technical skills of working with digital devices, includes cognitive and socio-behavioural competencies aimed at ensuring comfortable existence, effective communication and self-development of the person in the digital environment. Based on these competencies, the main development areas can be identified:

— digital skills and knowledge. For example, basic digital literacy, data analytics, machine learning, artificial intelligence, programming, IT system architecture, cybersecurity;

— skills and knowledge that help to cope with the future's volatility and uncertainty. For example, adaptability, critical and systemic thinking, stress management, change management, business planning, self-learning in accordance with the concept of "lifelong learning";

Table 2

Regression analysis results for the proposed model 1

Model	Non-standardized coefficients		Zero-order correlations	*t*-criterion	Relevance
	x, z	Standard error			
(Constant)	11,578	0,274		42,183	0,000
S — age	–0,008	0,004	–0,055	–2,206	0,027
X — number of years of production experience	7,032E–09	0,000	0,084	3,950	0,000
M — education	2,584E–08	0,000	0,030	1,820	0,069
G_e — gender	–0,495	0,084	–0,110	–5,901	0,000
B_o — profession	5,644E–08	0,000	0,155	8,831	0,000
Amur oblast	0,017	0,242	0,001	0,070	0,944
Astrakhan oblast	0,199	0,193	0,046	1,030	0,303
Belgorod oblast	–0,707	0,272	–0,052	–2,601	0,009
Bryansk oblast	–0,695	0,286	–0,046	–2,432	0,015
Vladimir oblast	0,275	0,275	0,027	1,000	0,317
Volgograd oblast	–0,426	0,315	–0,024	–1,352	0,177
Voronezh oblast	0,191	0,295	0,014	0,648	0,517
Ivanovo oblast	–0,134	0,295	–0,008	–0,453	0,650
Irkutsk oblast	0,381	0,265	0,027	1,439	0,150
Kaliningrad oblast	–0,243	0,400	–0,012	–0,608	0,544
Kemerovo oblast	–0,114	0,272	–0,007	–0,419	0,676
Kirov oblast	–0,070	0,287	–0,006	–0,244	0,807
Leningrad oblast	0,236	0,308	0,011	0,767	0,443
Lipetsk oblast	–0,332	0,249	–0,025	–1,330	0,184
Magadan oblast	–0,162	0,296	–0,013	–0,547	0,585
Moscow oblast	0,302	0,305	,023	0,992	0,321
Novgorod oblast	–0,321	0,257	–0,025	–1,249	0,212
Oryol oblast	0,439	0,305	0,033	1,437	0,151
Penza oblast	0,143	0,355	0,006	,403	0,687
Rostov oblast	–0,151	0,318	–0,007	–0,474	0,636
Saratov oblast	–0,001	0,239	0,002	–0,004	0,997
Sverdlovsk oblast	–0,475	0,334	–0,028	–1,425	0,154
Tyumen oblast	–0,411	0,307	–0,022	–1,340	0,180
Tula oblast	0,071	0,237	0,009	0,301	0,764
Yaroslavl oblast	0,186	0,279	0,012	0,669	0,503
Moscow	–0,066	0,340	–0,001	–0,195	0,845
St. Petersburg	0,376	0,369	0,017	1,018	0,309
Khanty-Mansi Autonomous Okrug — Ugra	0,152	0,357	0,012	0,426	0,670
Yamalo-Nenets Autonomous Okrug	0,096	0,342	0,001	0,282	0,778
Light industry	–0,567	0,228	–0,031	–2,486	0,013
Engineering	–0,288	0,298	–0,001	–0,965	0,335
Military-industrial complex	0,560	0,347	–0,019	–1,614	0,107
Oil and gas industry	0,060	0,287	0,013	–0,210	0,834
Metallurgy	0,310	0,278	–0,003	–1,115	0,265
Building	–0,318	0,204	–0,020	–1,556	0,120
Governing bodies	0,140	0,283	0,020	0,495	0,621

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Model	Non-standardized coefficients		Zero-order correlations	*t*-criterion	Relevance
	x, z	**Standard error**			
Education	–0,304	0,190	–0,018	–1,597	0,110
Finance and Insurance	0,015	0,296	0,012	0,050	0,960
Energy industry	0,414	0,317	–0,019	–1,304	0,192
R^2	0,059				
Adjusted R^2	0,046				
F — statistics	47,715				
Coefficient of Durbin — Watson	1,841				
Number of observations	3511				

— skills and knowledge that help to cope with a large flow of information, including basic programming, search, information processing and analysis, information hygiene, media literacy, and attention management;

— skills that define high communication abilities for effective interpersonal interaction. For example, the ability to work in a team, cooperation, self-presentation skills, business negotiation skills;

— skills that machines cannot master. For example, empathy and emotional intelligence, creativity and non-standard thinking, management of robotic processes.

Here are the results of the regression analysis on model 2 (Table 3).

Table 3

Regression analysis results for the proposed model 2

Model	Non-standardized coefficients		The standardized coefficients	*t*	Relevance
	ψ	**Standard error**	β		
Constant	11,127	0,444		25,077	0,000
Managers	1,085	0,447	0,023	2,425	0,015
Highly qualified specialists	–0,861	0,430	0,003	–2,003	0,045
Specialists of secondary qualification	–0,791	0,428	0,017	–1,846	0,065
Employees	–0,756	0,457	0,012	–1,652	0,099
Workers	–0,942	0,437	–0,011	–2,155	0,031
Labour using machines and mechanisms — manufacturing	–0,993	0,436	–0,016	–2,278	0,023
Intellectual production — brainfacturing	0,824	0,433	0,008	1,901	0,047
Unskilled workers	–0,863	0,440	–0,008	–1,960	0,050
Secondary general education	0,203	0,179	0,013	1,132	0,258
Higher professional education	0,042	0,104	–0,006	0,403	0,687
Foreign language Skills	0,087	0,116	0,020	0,749	0,454
BigDate Skills	0,231	0,191	0,028	1,211	0,226
Digital Skills	–0,116	0,186	0,020	–0,622	0,534
Family status	0,152	0,116	0,014	1,320	0,187
Presence of children	–0,093	0,129	–0,011	–0,716	0,474
Missing days of work due to illness	0,324	0,112	0,044	2,882	0,004
R^2	0,009				
Adjusted R^2	0,004				
F — statistics	71,588				
Coefficient of Durbin — Watson	1,774				
Number of observations	3511				

Discussion of the results

The age determinant. The distribution chart of average wages by the age groups demonstrates that age affects wages mainly in the range of 20 years, with the inflection point being between the ages of 31 and 32 years, followed by the decrease (Figure 2).

A significant drop in salaries in the 22–25-year period is observed among employees of high-tech industries, which confirms that in the digital economy by 2025, the generation Z (1997 birth year and younger) will occupy about 25 % of all working places.

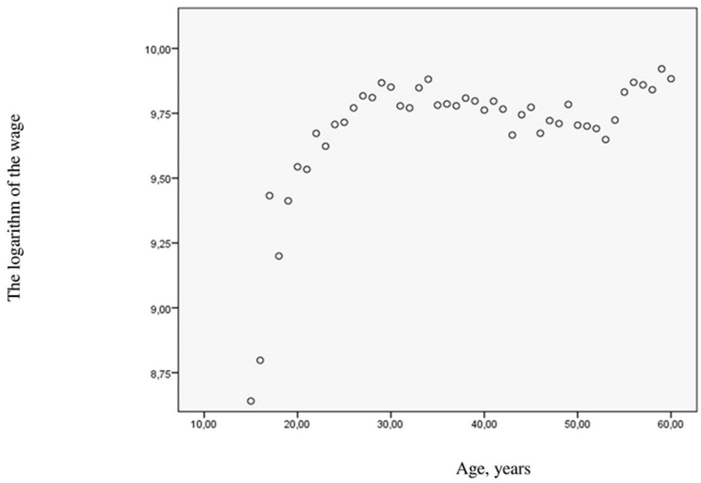


Fig. 2. *Wage logarithm dependence on age, 2016*

The transition to digital technologies involves the processes' flexibility and individualization, alteration of the structure and corporate culture, optimization of the management model in the digital reality, transformation of curricula, etc. Global integration processes and trends in the widespread introduction of the digital technologies inevitably challenge the need to take into account the phenomenon of the "new generation". M. Prensky gave the most successful definition to that generation of students calling them Digital Natives (digital born). The processes taking place directly in universities are crucial: the introduction and development of new technologies and the digitalization are directly related to internationalization, as the university's digitalization will make it more adapted for a new generation of students or digital natives. This will definitely increase the university's attractiveness in the educational space on the regional level, and on a larger scale.

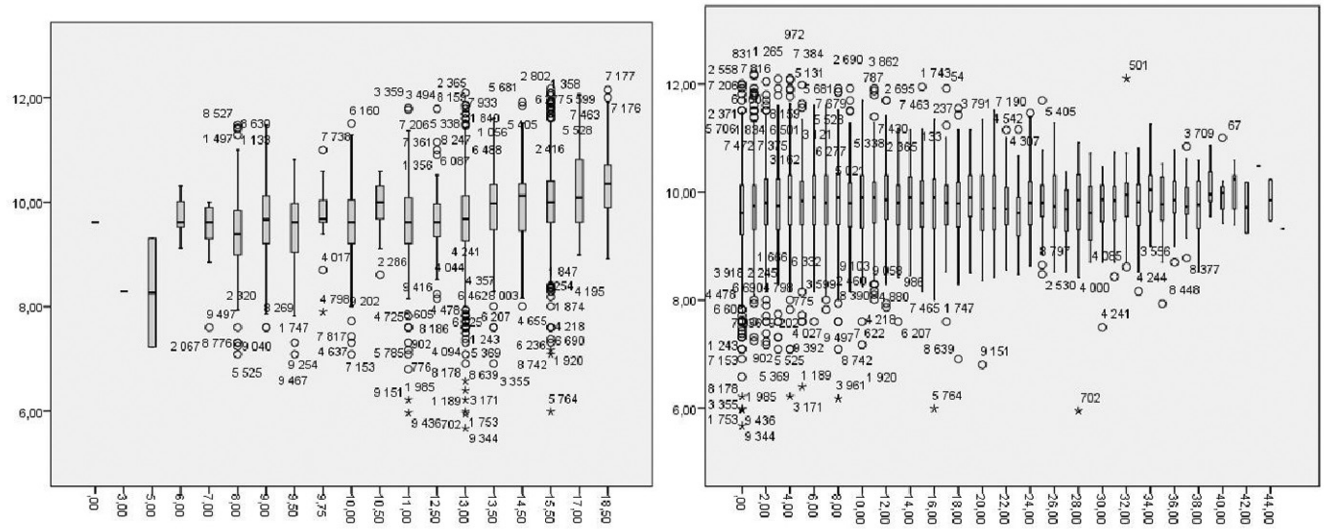
The contribution of this indicator compared to other qualitative parameters remains negligible, it is crucial for understanding the main trends of the human capital's efficient use in the digital economy. Using the data of the RLMS on the detailing of the education level, we supplemented our research with an empirical assessment of the number of accumulated years of education, including special courses, etc.

The determinant of education. The impact of this factor reflects the individual return of each accumulated year of education and illustrates that the return on individual human capital of workers is lower than the social returns of those employed in the digital economy (Figure 3). Young people up to the age of 30 have the greatest return on formal education in the structure of the employed, as the efficiency of the use of human capital is lower for the worker older than 31 years. This confirms the digital economy's demand for new approaches to a growing group of perpetual students in the education system, as the results of the continuing demographic changes in the digital environment will significantly influence the existing workforce environment: older people will need to relearn over a longer life, moreover, the demand for new skills and additional services will appear.

The existing traditional education system does not satisfy the current demand for high-quality human capital in digital technology. Russian education system lags far behind the digital leaders, which creates risks of a shortage of digital personnel in the future. Despite the fact that, according to Times Higher Education, the number of Russian educational institutions in the list of world's 980 best universities has doubled in the last year and reached 24, Russia is far below such digital leaders as the USA (148) and the United Kingdom (91), as well as catch-up countries such as China (52) and Brazil (27). At the same time, none of the Russian universities are included in the Top 100 list, while China is represented by five universities.

It is clear that the traditional model of education, aimed only at learning, is hopelessly outdated. There is a need to transform the very paradigm of education and to rethink the existing approaches and learning models in order to develop shared digital literacy, social and emotional skills for succeeding in the new digital world.

The Determinant of Production Experience reflects the ability of enterprises to reproduce human capital by investing in formal education, such as retraining in the workplace or additional short-term



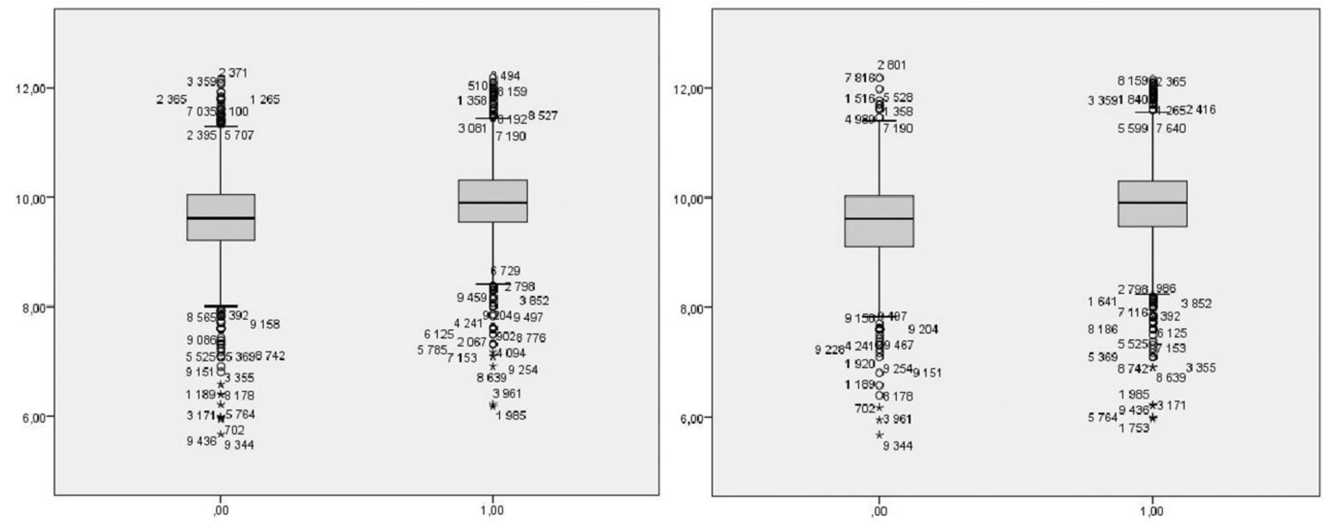
a) A box diagram of the wage logarithm as a function of educational attainment

b) A box diagram of dependence of the wage logarithm on the work experience

Fig. 3. *The impact of education factors and experience on the return of human capital in the form of a wage logarithm (the emission number reflects the figure; emissions are marked by circles; extreme emissions are marked by an asterisk)*

courses. The existing dependence on the efficiency of the use of human capital in the form of a wage logarithm from each year of production experience is unstable as there is no clear pattern. The return on the work experience of the employed population aged 15–30 years is 2–4 %, and with age, the regression rate ceases to be significant.

Thus, the hypothesis about the impact of industrial experience on wages as an indicator of the return of human capital, previously put and supported by J. Mincer and his followers, is not confirmed in the digital economy. For digital technologies, replacement of the old methods of working makes old skills and organizational approaches irrelevant. Transformations caused by the environment's automation and digitalization change the working activities from clearly defined work responsibilities to project work. Organizations hire the majority of people for well-defined jobs when the nature of responsibilities does not change significantly. However, gradually the marketing, finance and other functions cease to be limited to certain functional requirements and move to design and team self-organization. As a result, the organizational structure is changing: new work tasks, defined by the technologies that go beyond the functions of units, have much shorter, project-oriented time frames and can radically change the ways of working depending on the project. An important factor in the



a) A box diagram of gender dependence of the wage logarithm

b) A box diagram of the dependence of the wage logarithm on the region

Fig. 4. *The impact of the gender and regional determinants on the return of human capital in the form of wage logarithm*

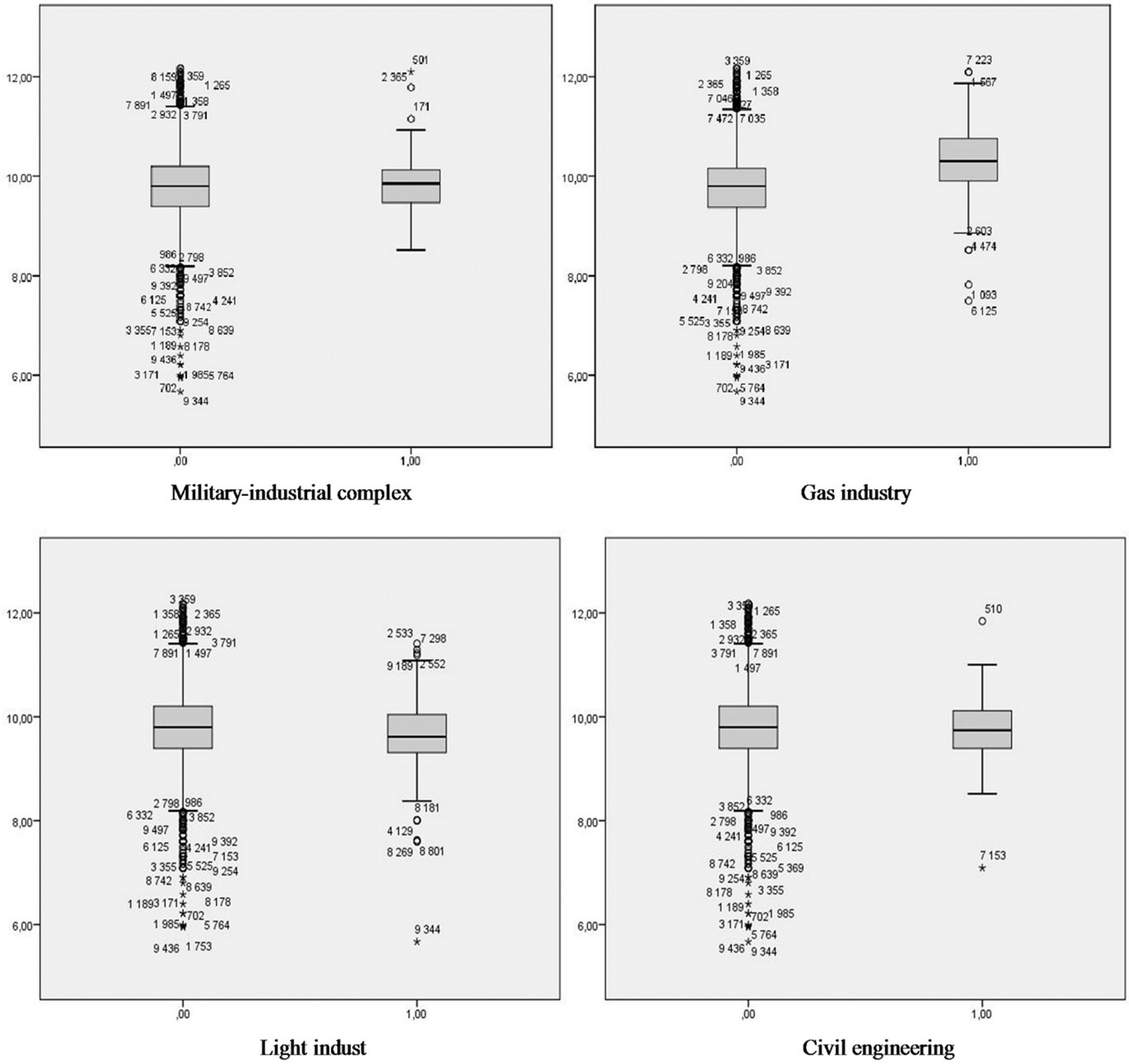


Fig. 5. *The impact of industry determinants on the return of human capital in the form of wage logarithm*

efficiency of the use of human capital in the digital economy is the development of digital knowledge skills that enable workers to adapt to the changed workflows and demands of employers.

The determinant of gender is one of the most influencing factors for the statistical significance, as women get more returns for each year of education (Figure 4).

The regional determinant. Our regression analysis has shown that there is an uneven distribution of wages in the regional structure. Therefore, there is a high efficiency of investments in mobile individual human capital that manifests itself in a search for work in the regions with adequate infrastructure that can bring maximum returns from the implementation of their own knowledge and skills in the labour market.

Observed trends in the indicators reflecting territorial differentiation are explained, on the one hand, by the large concentration of capital in the development of the regional labour market that shapes its competitiveness contributing to the increase in efficiency of the human capital use. At the same time, the level of the digital infrastructure's development in different regions varies considerably: for example, the average connection speed in Moscow and St. Petersburg is much higher, and tariffs for the population are more affordable than in medium and small cities. Developed infrastructure is the foundation of the digital economy. Businesses that are actively implementing digital technologies demonstrate higher financial results of profitability and revenue and, as a result, high earnings of employees. According to a study by the McKinsey Global Institute, in China, where the potential for rapid growth through large investments and employment growth will sooner or later be exhausted, between 7 % and 22 % of gross domestic product's total growth will come from the use of digital technologies by 2025. In the United States, the cost increase from the introduction of digital technologies could reach $1.6–2.2 trillion by 2025.

The industry determinant. In the first regression model, six industries represent the industry factor; the sensitivity of four of them is demonstrated in the diagram charts (Figure 5).

Because of the limited number of observations in some industries, it is difficult to have an in-depth regression analysis of the return on human capital. In this regard, it is necessary to assess the significance of the impact on the corresponding regression equation factor (t-statistics); positive regression rates have oil and gas, military-industrial, energy, heavy industries, as well as such employment areas as government and finance.

This confirms the fact that the digital economy is creating an increased demand for high-quality human capital in the "knowledge" category.

The second proposed model included qualitative parameters, so let us assess the results.

The determinant of the qualification level of workers has a positive effect on wages, which is quite obvious and only emphasizes this hypothesis. A significant factor at the 0.01 level is the status of the manager as it has the greatest impact among those considered. In skilled labour, intellectual labour at the 0.05 level is the most important, as in comparison with mechanized labour, it has positive regression factor. This confirms that the key characteristic of the digital economy is the structure of the labour market, in which more than 25 % of employees work in the so-called "knowledge" category. Employees of the category of "knowledge" are those whose work with a share of more than 50 % requires analytical work, improvisation in conditions of uncertainty, a high level of autonomy in the decision-making process. Their training requires a high level of education in a long cycle of study.

As automation increases, the demand for highly skilled workers in the "knowledge" category will increase dramatically, and there are at least four areas where significant changes can occur:

— The technology sector as a result of the next-generation technologies' development for industrial and consumer applications (e.g. design and programming of smart energy networks and other smart systems for cities and households, or the production of urban robotics and unmanned autonomous vehicles, or the design and production of renewable bioengineering materials);

— Human-oriented services that will affect areas beyond the control of automation (personalized services in the spheres of education, healthcare, experience design, entertainment, etc.);

— Virtual economics, including areas of activity in different virtual environments (e.g. virtual reality, social networks);

— Creative economy, aimed at creating innovations as a result of the creative process based on new technologies, in particular, various software for content processing, virtual reality, etc.

The determinant of competence includes foreign language skills, BigDate Skills, and the use of digital skills. The widespread of technology and the Internet access has led to an exponential increase in the amount of data generated. According to IDC1, by 2017, the world has accumulated 16 zettabytes of data (1 zB = 1,024 exabytes, 1 EB = 1 billion gigabytes), and by 2025 this figure will increase to 163 zettabytes. Using the huge amounts of data, organizations have additional opportunities to grow and expand their businesses. However, the acute question on how to manage, analyse and extract useful value from raw data arises. More companies are starting to use machine-learning algorithms to improve sales efficiency, personalise customer experience, optimise processes, and generate strategic ideas based on big data analysis. By Digital Skills, we understand established, automatized patterns of behaviour based on knowledge and skills in the use of digital devices, communication applications and networks to access information and manage it. Digital skills enable people to create and share digital content, communicate and solve problems for effective and creative self-fulfilment in learning, work and social activities in general.

The ongoing shift of emphasis on the development of composite integrated skills of cooperation and communication in the digital environment as opposed to narrowly understood computer literacy is worth noting. It is important to consider digital skills, which encompass technical knowledge in ICT, in close relation to soft skills and general knowledge. For example, this approach vividly illustrates the "Target Competence Model 2025" prepared by BCG based on the consensus opinion of experts and analysis of the approaches of the Lominger Competence Library, Sberbank, RosExpert / Korn Ferry, HSE, WorldSkills Russia and Global Education Futures. This model, in addition to the purely technical skills of working with digital devices, includes cognitive and socio-behavioural competencies aimed at ensuring comfortable existence, effective communication and self-development of the person in the digital environment.

Possession of these competencies results in an increase in wages from 14 to 22 % across all spheres of activity. For certain spheres of activity this indicator is unstable, for example, in the military-industrial complex it is negative, while in the oil and gas and energy industries it has the maximum positive value. In general, the results for the competent determinants of human capital required for the digital economy yield the greatest returns. The importance of digital skills for working and social integration is increasing, and they will be vital in the future. Thus, the formation of high-quality human capital with developed digital competencies at different levels and its effective use in the company will provide it with a competitive advantage.

The practical significance of the results is that the correct interpretation of the determinants influencing the efficiency of the use of human capital will allow us to choose the right tools for managing it as a factor of economic growth. This study is the starting point for a large-scale work aimed at identifying the new vectors in the strategic management of processes related to the accumulation and use of human capital in the digital economy's development.

References

1. Abakumova, I. V., Antonova, E. K., Baigulov, R. M., Belyaeva, S. V., et. al. (2016). *Nauchnye issledovaniya v sfere sotsialno-ekonomicheskikh i gumanitarnykh nauk: mezhdistsiplinarnyy podkhod i konvergentsiya znaniy [Scientific research in the field of socio-economic sciences and humanities: an interdisciplinary approach and convergence of knowledge].* Samara: Ofort, 416. (In Russ.)

2. Baigulov, R. M. & Podkopaeva, O. A. (Eds.). (2016). *Rezultaty sotsialno-ekonomicheskkih I mezhdistsiplinarnykh nauchnykh issledovaniy XXI veka [Results of socio-economic and interdisciplinary scientific researches of the XXI century].* Samara: Ofort, 434. (In Russ.)

3. Abasheva, O. Yu., Babina, E. N., Bondarenko, G. V., et. al. (2018). *Prikladnye, poiskovye i fundamentalnye sotsialno-ekonomicheskie issledovaniya: integratsiya nauki i praktiki [Applied, exploratory and fundamental socio-economic research: the integration of science and practice].* Samara: Ofort LLC, 244. (In Russ.)

4. Boyarov, A. D., Volkova, M. N., Garafiev, I. Z., Chernov, S. S., Chirkova, M. B., et. al. (2009). *Problemy ekonomiki i upravleniya predpriyatiyami, otraslyami, kompleksami [Problems of economics and management of enterprises, industries, complexes].* Novosibirsk: Center for the Development of Scientific Cooperation, 346. (In Russ.)

5. Auzan, A. (2015). Effekt kolei. Problema zavisimosti ot traektori I predshestvuyushchego razvitiya — evolyutsiya gipotez [Path dependence problem: the evolution of approaches]. *Vestnik Moskovskogo Universiteta. Seriya 6. Ekonomika [Moscow University Economics Bulletin], 1,* 3–17. (In Russ.)

6. Balatsky, E. V. (2000). Diskont-faktor v raschetakh rentabelnosti vlozheniy v chelovecheskiy kapital [Discount factor in calculating the profitability of investments in human capital]. *Obshchestvo i ekonomika [Society and Economics], 11–12,* 93–103. (In Russ.)

7. Kapelyushnikov, R. I. (2004). Politika zarabotnoy platy rossiyskikh predpriyatiy [The salary policy of Russian enterprises]. *Vestnik obshchestvennogo mneniya. Dannye. Analiz. Discussii. [The Russian public opinion herald. Data. Analysis. Discussions], 4,* 48–69. (In Russ.)

8. Kapelyushnikov, R. I. (2006). Obrazovatelnyy potentsial i ego svyaz s kharakteristikami rynka truda: rossiyskiy opyt [Human capital accumulation and the labor market outcomes: evidence from Russia]. *Ekonomicheskaya politika [Economic policy], 4,* 166–195. (In Russ.)

9. Shirinkina, E. V. (2017). Otsenka effektivnosti ispolzovaniya obrazovatelnogo kapitala kak dominiruyushchego elementa chelovecheskogo kapitala v ekonomike znaniy [Evaluation of the effectiveness of the use of educational capital as the dominant element of human capital in the knowledge economy]. *Ekonomika i predprinimatelsvo [Journal of Economy and Entrepreneurship], 4–2 (81–2),* 854–861. (In Russ.)

10. Becker, G. S. (1964). *Human Capital: A Theoretical and Empirical Analysis.* New York: Columbia University Press for NBER, 346.

11. Leslie, L. & Brinkman, P. (1988). *The Economic Value of Higher Education.* New York: Macmillan Publishing Company, 288.

12. Mincer, J. (1985). Intercountry Comparisons of Labor Force Trends and of Related Developments: An Overview. *Journal of Labor Economics, 3(1),* 1–32.

13. Mincer, J. (1962). On-the-Job Training: Costs, Returns, and Some Implications. *Journal of Political1 Economics, 70(5),* 50–79.

14. Psacharopoulos, G. & Patrinos, H. A. (2004). Returns to investment in Education: a further update. *Education economics, 12(2),* 105–111.

15. Lin, S.-C. & Huang, Y.-M. (2005). The role of social capital in the relationship between human capital and career mobility. *Journal of Intellectual Capital, 6(2),* 191–205.

16. Vryonides, M. & Lamprianuou, I. (2013). Education and social stratification across Europe. *International Journal of Sociology and Social Policy, 33(1/2),* 77–97.

17. Chernenko, I. M. (2014). *Strategicheskoe upravlenie chelovecheskim kapitalom promyshlennogo predpriyatiya [Strategic human capital management of an industrial enterprise].* Ekaterinburg: UrFU, 315 p. (In Russ.)

18. Kapelyushnikov, R. I. (2009). *Transformatsiya chelovecheskogo kapitala v rossiysskom obshchestve [Transformation of human capital in Russian society].* Moscow: The Liberal Mission Foundation, 196. (In Russ.)

19. Kapelyushnikov, R. I. (2013). Upala li ekonomicheskaya otdacha ot obrazovaniya? [Whether economic return from education fell]. *Ekonomika obrazovaniya [The Economics of Education],1,* 44–50. (In Russ.)

20. Karatkevich, S. G., Dobrynin, V. N. & Bagretsov, S. A. (2011). Sistema pokazateley otsenki chelovecheskogo kapitala [The system of indicators of assessing human capital]. *Voprosy ekonomiki I prava [Economic and Law Issues], 7,* 76–78. (In Russ.)

Translation

21. Gvozdeva, M. A., Kazakova, M. V., Lyubimov, I. L. & Nesterova, K. V. (2017). Immigratsiya, shkolnaya sistema i nakoplenie chelovecheskogo kapitala [Immigration, school system and human capital]. *Ekonomicheskaya politika [Economic Policy], 1,* 40–57. (In Russ.)

22. Prokushev, E. F. (2008). *Otsenka chelovecheskogo kapitala organizatsii [Assessment of the human capital of the organization].* Belgorod: Cooperative Education, 125. (In Russ.)

23. Sumarokova, E. V. (2002). *Metodologiya issledovaniya protsessa investirovaniya v chelovecheskiy kapital [Methodology of investing in human capital].* Moscow, 190. (In Russ.)

24. Shirinkina, E. V. (2017). Kiberneticheskiy podkhod k ispolzovaniyu chelovecheskogo kapitala [Cybernetic approach to the use of human capital]. In: *Fundamentalnaya nauka I tekhnologii — perspektivnye razrabotki. Materialy XII mezhdunarodnoy nauchno-prakticheskoy konferentsii [Fundamental science and technology — promising developments. materials of the XII international scientific and practical conference]* (pp. 198–200). North Charleston, USA. (In Russ.)

25. Kelchevskaya, N. R., Chernenko, I. M. & Shirinkina, E. V. (2017). *Chelovecheskiy kapital v usloviyakh integratsii obrazovatelnykh I professionalnykh standartov [Human capital in the context of the integration of educational and professional standards].* Perm, 220. (In Russ.)

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