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TECHNOLOGICAL DEVELOPMENT AND EMPLOYMENT STRUCTURE IN CONTEXT OF ECONOMY DIGITAL TRANSFORMATION

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Abstract

The article examines the influence of the technological changes on the labor market formation and employment in new forms. It is shown that the employment structure will develop under the increasing influence in market demand for highly qualified workers and wide diffusion of employment alternative forms. Market demand for highly skilled workers in the digital age will grow for several reasons. First, digital technologies can be expected to create a significant number of new jobs in big data analytics, training and management of artificial intelligence, intelligent computing technologies and software development, training, maintenance and management of intelligent robots. Secondly, there is always a new technologies diffusion indirect effect when new jobs are created in related industries. Jobs in these emerging industries will require deep and versatile math, engineering knowledge, job skills that can only be gained through successful graduate and postgraduate studies. Conversely, digital technologies create new opportunities for finding and organizing work for a potential employee, which has already formed a significant market for employment alternative forms. In this regard, the authors aimed to create a mathematical model of jobs technological substitution in the digital economy and to assess the labor force distribution across three forms of employment (full employment, contingent employed and employed on electronic platforms) in economy digital transformation context. For the first time, the authors proposed mathematical models of labor force distribution for three forms of employment, probability distribution curves of labor force technological replacement depending on employment form in context of economy digital transformation.

Keywords: Digital technologies, labor market, models and distribution curves

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1. Introduction

In the last two centuries, economic development is connected with science and education progress. Their close connection provided the production material sectors, and at later development stages and the service sector, with new technologies and materials, it was possible to achieve rapid transformations in the economic and social spheres. At the same time, the relationship between technological progress and employment has always been complex and ambiguous. At the company and firm level, new technologies tended to result in job losses. At the level of individual sectors and the national economy as a whole, this negative effect was offset by institutional factors (such as government intervention or shifts in spatial distribution) or market mechanisms (internal labor migration, the creation of new firms). The economic literature contains quite many works describing the mechanisms of interaction between new technologies and employment (Arntz et al., 2016; Autor & Salomons, 2018; Bessen, 2018; Graetz & Michaels, 2018).

It is to be expected that the impact of new technologies on the employment system will only increase with the transition to the digital economy. The milestone in the digital economy emergence is considered to be 2007, when the mobile Internet started working, which developed so rapidly that by 2017 it occupied almost half of all Internet traffic in the world. During this period, breakthroughs have occurred in key digital technologies - cloud computing, big data analytics, artificial intelligence (A.I.), the Internet of things (IoT), blockchain and A.I. robotics, as well as intelligent computing technologies. The world started talking about the onset of the 4th industrial revolution and the digital economy formation (Schwab, 2016). Today, in a number of developed and avant-garde developing countries of the world, the digital economy foundations have already been laid, which has now become one of the economic growth main driving forces. The digital economy growth rate in the leading countries (USA, Japan, U.K., China, etc.) over the past 5 years averaged 5-7% per year (Huaten, 2019). Thus, the digital economy is already helping to increase labor productivity in production, creating new markets and new points of economy growth, significantly changing the structure of the labor market itself. Therefore, it is quite natural to expect an increase in the the digital economy knowledge intensity as a whole, which implies an increased demand for highly qualified specialists from the STEM sector (Science, Technology, Engineering, Mathematics).

At the same time, the global digital infrastructure formation has created new opportunities for creating a new type of employee-employer relationship. This has found its expression in more developed alternative employment forms, such as: contractors, external part-time and independent workers, employees hired on electronic platforms. At present, all these employment forms are defined as "contingent labor force", which is formed by two main groups: "temporary employment" and "part-time employment". According to OECD estimates, in 2018, the average for the organization, the first indicator was at the level of 11.7% of those with permanent contracts. However, in countries such as Croatia, Korea, the Netherlands, Portugal, Poland, Spain, Chile and Colombia, the figure ranged from 20 to 28.8 percent (OECD, 2020a). As for the second indicator, in 2018 its average value was 16.5% of all employed, but there were also strong deviations from this value: Germany, Great Britain, Japan, Australia, Switzerland and the Netherlands had this indicator ranging from 22 up to 37.3 percent (OECD, 2020b). If we consider the geographically broader regions, then, according to experts, the "contingent

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labor force" in the first quarter of 2018 in Europe, the Middle East and Africa was about 15.25% of the total labor force, or 68.7 million. people, in the USA their number was about 23.6 million people in 2015. or 16% of the total labor force (Katz & Krueger, 2016; ManpowerGroup, 2018). The Sharing Economy is becoming an important component of the emerging digital economy. The technological basis of the latter is digital platforms, which have opened up new opportunities, both for doing business and for the employees themselves (Degryse, 2016; Valenduc & Vendramin, 2016). Therefore, one of the main changes in the labor market over the past decade has been the emergence of online electronic job search platforms. Thus, clusters of digital technologies are able to radically change the already established labor markets, which can significantly affect the growth rate of the world economy as a whole. In this regard, the purpose of our study is to model and assess the distribution of the labor force in three forms of employment (full employment, contingent employed and employed on electronic platforms) in the context of the digital transformation of the economy.

2. Problem Statement

An early and pioneering study, published in 2003, noted that mid-level manufacturing and clerical professions are characterized by a high intensity of rule-based procedures that can be characterized as "routine tasks" and which can be relatively easily replaced by computer programs. (Autor et al., 2003). Rapid advances in information and communications technology, beginning in the early 1980s, have accelerated the automation of such routine tasks, enabling the start of the replacement process in many mid-range activities such as accounting, clerical work and batch production. As a result, the relative general economic demand for ordinary middle-level occupations has dropped significantly. At the same time, a significant layer of non-standard manual cognitive tasks remained in the economy, which are difficult to replace with machines or programs (for example, driving a car or cleaning an office). These trends in the labor market, caused by technological factors, occurred against the backdrop of a significantly increased educational level of those employed in the economy. For example, in the American economy, the those employed share in the economy with a secondary education in 1985 amounted to 73.9% against 24.5% in 1940 and subsequently increased to 89.8% in 2018[1]. In parallel with this, in countries In Europe and the American economy, there was an increasing gap in the workers' pay levels with high and intermediate qualifications (with secondary education and graduated from colleges or universities): in 2008, the latter in the United States earned an average of 97% more than the former, although in the early 1980 the gap was no more than 15-20 percent (Acemoglu & Autor, 2011). The decline in professions based on the routine operations performance has led to the labor market of specialists washing out of average skill and their concentration in two zones - in the zone of highly skilled and highly paid labor, as well as in the zone of low-skilled and low-paid labor. This new social phenomenon has been termed the "polarization of the labor force" (Autor & Dorn, 2013). In the American economy, every third person worked in the segment of routine operations in the 1980s, now every fourth employed and the peculiarity of such professions has become their non-recoverability after

[1] U.S. Department of Education, National Center for Education Statistics (2019). Table 104.10. Rates of high school completion and bachelor's degree attainment among persons age 25 and over, by race/ethnicity and sex: Selected years, 1910 through 2018. [Data file]. Retrieved from https://nces.ed.gov/programs/digest/d18/tables/dt18_104.10.asp

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the economic crises since 1991, which was not observed during the crises of 1970-1980. x years (Siu & Jaimovich, 2012). The polarization process accelerated after the 2000s. This was facilitated by the emergence of computer technologies with elements of artificial intelligence, which began to replace people already in such areas that required advanced cognitive activity, such as the provision of financial or legal services, education and medicine. Indeed, the new technological leap was provided by a number of disruptive technologies. NBIC technologies have spread rapidly and technologies of the 4th industrial revolution and Industry 4.0 itself became a practical reality (Schwab, 2016; Schwab & Davis, 2018). At the same time, the industrial Internet is becoming the basic infrastructure of Industry 4.0 - a digital platform that ensures effective interaction of all industrial production facilities based on the Internet. With the advent of intelligent robots, they will be widely used in most spheres of public life and the economy. A multifunctional digital information technology Blockchain was also created, designed for reliable accounting of assets and transactions with them. All these technologies together form a new, digital infrastructure that can significantly change the entire economic landscape. This new stage of technological development will be associated with the disappearance of many traditional professions. Most low-skilled service jobs will remain for humans only because it is economically unprofitable to replace them with expensive, intelligent machines. In this regard, it should be expected that a significant part of workers of average skill in the future can only rely on low-paid jobs in the service sector. For example, in the American economy, the service sector (retail; health and social assistance; and leisure and hospitality) employs about 48 million people, of which 62% have limited literacy skills, 74% have limited numeracy skills, and 73% lack digital skills (Bergson-Shilcock, 2017). It should also be borne in mind that in the service sector itself, low wages, heavy work schedules and limited opportunities for career development, and in the event of large economic shocks (like the COVID-19 pandemic), the threat of job loss becomes a reality for 15 percent of employees (Kochhar & Barroso, 2020)[2]. To avoid such a scenario of development and to maintain the demand for representatives of the middle class with medium-high qualifications, it is necessary to make significant adjustments to the practice of education and training of specialists in order to ensure that new requirements for workers coincide with the level of their professional training.

3. Research Questions

Market demand for highly skilled workers in the digital age will grow for a number of reasons. First, digital technologies can be expected to create a significant number of new jobs in areas such as big data analytics, training and management of artificial intelligence, development of intelligent computing technologies and software, training, maintenance and management of intelligent robots. Secondly, there is always an indirect effect of the diffusion of new technologies, when new jobs are created in related industries. Jobs in these emerging industries will require the deep and versatile math and engineering knowledge and job skills that can only be gained through successful graduate and postgraduate studies. Today, for example, the high-tech sector in the United States employs about 2.9 million people (1.9% of

[2] Industries with a higher risk of employment loss include: food services and drinking places (9.7 million); accommodation (1.5 million); arts, entertainment, and recreation (3.4 million); child day care services (1.5 million); personal and laundry services (2.7 million); retail trade (16.2 million); and selected transportation industries (3.1 million).

all employed), in Germany, this sector employs about 2.4% of the workforce. As the McKinsey Global Institute predicts, an increase in spending on technology will create by 2030, within the global economy, a demand for 20-46 million additional, mostly highly skilled, workers, half of which will be in countries such as China, Germany, India, the Netherlands and the United States. At the same time, it is expected that by the same time about 30% of the total working time fund will be automated (Manyika et al., 2017). The U.S. Department of Labor predicts that by 2024 new jobs will be created for the following STEM jobs: ICT (+76%), Mathematics (+7%), Science (+6%), Engineering (+11%)[3].

The world today is experiencing a new stage in the labor market evolution, caused by the transition to a high-tech and knowledge-based economy. Currently, knowledge-intensive industries are divided into two subgroups: based on advanced technologies (Leading-edge technology), when internal expenditures on R&D from the cost of sales are at least 9%; and high technologies (High-level technology), when internal expenditures on R&D from the cost of sales are at least 3% (Gehrke et al., 2012). It should be noted that almost all technologies that form the new, digital economy are advanced. And this is primarily due to the fact that these technologies are associated with the knowledge generation based on investments in human capital (Gehrke et al., 2012). Therefore, one should expect an outstripping growth in spending on science and education. It is also necessary to take into account the fact that the R&D sector uses "rare factors of production" - highly qualified workers, researchers and scientists. Consequently, the growing knowledge-intensiveness of the digital economy also creates an increased demand for highly qualified specialists from the STEM sector (Danish Technological Institute, 2015).

Thus, technological development significantly affects the labor market state and its structure, and in the digital transformation context, a wide diffusion of new technologies, and, consequently, the replacement of living labor by machines, should be expected in the intermediate skilled labor segment.

4. Purpose of the Study

This paper sets two goals:

- to propose a mathematical model for jobs technological replacement in the digital economy;
- to evaluate, based on the model, the labor force distribution in three employment forms (full employment, contingent employed and employed on electronic platforms) in the economy digital transformation context.

5. Research Methods

Today, the digital economy share in developed countries is approximately 5-10%. It is estimated that the digital transformation of the entire economy will take approximately 10-12 years (Huaten, 2019; Schwab, 2016). Consequently, already in the 2030s, in most countries of the world, the digital economy will function on a significant scale, and the main trend in the development of industry will be the transition to a fully automated digital industry 4.0.

[3] Bureau of Labor Statistics, U.S. Department of Labor (2015). EMPLOYMENT PROJECTIONS — 2014-24. Retrieved from www.bls.gov/emp/ep_table_102.htm

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The initial assumptions when building the model are that human capital is formed based on received income and can be described using the formula (Jones & Vollrath, 2013):

$$h=\exp(\psi\cdot u) \#(1)$$

where h – knowledge and skills stock (human capital), u – average number of study years; ψ – return rate on education. According to (Acemoglu, 2009; Jones & Vollrath, 2013), empirical estimates of the coefficient $0.06\leq\psi\leq0.1$ mean that an education additional year increases human capital by 6-10%.

Another assumption of the study is that the distribution of the labor force in traditional employment obeys the normal law (Monsik & Skrynnikov, 2012, p. 127-128). Denoting the distribution of the relative labor force by skill level $l(h)=\frac{L_h}{\bar{L}}$ (where L_h is the number of labor force with skill level h; $\bar{L}$ is the total number of labor resources), we express the distribution of the effective labor force by skill levels:

$$l_{ef}(h)=h\cdot l(h)\#(2)$$

To describe the jobs technological replacement process in the digital economy, let us denote *p(h)* the probability of replacing a labor force with a skill level *h* using an intelligent machine (I.M.). Since it is economically unprofitable to replace low-skilled workers who are engaged not in physical but in cognitive routine labor activity at the current level of I.M., the replacing probability of such low-skilled labor force can be taken equal to zero, i.e.:

$$p(h)=0, \text{ for } h_m\leq h\leq h_3\#(3)$$

Assuming the medium-skilled workers active replacement with I.M. and a gradual transition to the highly-skilled workers replacement, let us take the workers replacement probability in the lower segment of the average skill $h>h_3$) close to one ($p(h_3)\approx1$), and the replacing researchers probability ($h\geq h_M$) is close to 0 ($p(h_M)\approx0$).

Assuming the logistic law of the substitution process, we obtain the following distribution curve describing the labor force technological substitution probabilities in the current decade:

$$p(h)=\begin{cases} 0, \text{ for } h_m\leq h\leq h_3; \\ \dfrac{1}{1+exp\left[\vartheta_h\cdot\left(h\text{-}\dfrac{h_3+h_M}{2}\right)\right]}, & h_3\leq h\leq h_M \end{cases}\#(4)$$

Where the parameter ϑ_h is found from the condition $p(h_3)\approx1;\ p(h_M)\approx0$.

Further, the effective labor force employed distribution in the economy after the digital transformation completion in the 2030s can be written as:

$$l_{efe}(h)=[1\text{-}p(h)]hl(h)\#(5)$$

The effective workers shares of low (l), medium (m) and high (h) qualifications before (λ_{ef}) and after (λ_{efe}) digital transformation are calculated by the formulas:

$$\begin{aligned} &\text{a) } \lambda_{ef}^{(l)}=\frac{\int_1^{h_3} hl(h)dh}{\int_1^{h_M} hl(h)dh};\ \lambda_{efe}^{(l)}=\frac{\int_1^{h_3}[1\text{-}p(h)]hl(h)dh}{\int_1^{h_M}[1\text{-}p(h)]hl(h)dh} \\ &\text{b) } \lambda_{ef}^{(m)}=\frac{\int_{h_3}^{h_4} hl(h)dh}{\int_1^{h_M} hl(h)dh};\ \lambda_{efe}^{(m)}=\frac{\int_{h_3}^{h_4}[1\text{-}p(h)]hl(h)dh}{\int_1^{h_M}[1\text{-}p(h)]hl(h)dh}\#(6) \\ &\text{c) } \lambda_{ef}^{(h)}=\frac{\int_{h_4}^{h_M} hl(h)dh}{\int_1^{h_M} hl(h)dh};\ \lambda_{efe}^{(h)}=\frac{\int_{h_4}^{h_M}[1\text{-}p(h)]hl(h)dh}{\int_1^{h_M}[1\text{-}p(h)]hl(h)dh} \end{aligned}$$

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Formulas (1-6) form a complex for analyzing the labor force distribution to describe digital transformation impact on labor market.

6. Findings

As a basis for verifying the proposed model, we use data from the U.S. Federal Bureau of Labor Statistics for 2017[4,5,6].

The workers' shares distribution of various categories by education is presented in table 1.

Table 1. Workers share by educational attainment in the U.S. economy

Education levels	h	Workers (%)			
		Contingent	With an alternative work arrangement	Noncontingent, with traditional work arrangement	Electronically mediated
Less than a high school diploma	1÷2.05	7	9.6	7	4.4
High school graduates, no college	2.05÷3.2	25.2	26.1	25	19.7
Some college or associate degree	3.2÷4.57	27.2	27.0	27	26
Bachelor's degree and higher:	4.57÷8.17	40.6	37.3	41	49.9
Bachelor's degree only	*4.57÷6.05*			*25*	*27.9*
Advanced degree	*6.05÷8.17*			*16*	*22*

According to the testing the hypothesis of a normal distribution results (with a significance level of $\alpha = 0.05$) for workers with traditional employment, the Pearson's statistics observed value (5.24) does not fall into the critical region (5.99146). Thus, the labor resources distribution with traditional employment is normal with the mathematical expectation h_μ=4.27 and the standard deviation σ_h=1.673.

4 U.S. Department of Labor, Bureau of Labor Statistics (2018, June). Table 3. Employed contingent and noncontingent workers by school enrollment and educational attainment, May 2017 [Data file]. Retrieved from https://www.bls.gov/news.release/conemp.t03.htm

5 U.S. Department of Labor, Bureau of Labor Statistics (2018, June). Table 7. Employed workers with alternative and traditional work arrangements by school enrollment and educational attainment, May 2017 [Data file]. Retrieved from https://www.bls.gov/news.release/conemp.t07.htm

6 U.S. Department of Labor, Bureau of Labor Statistics (2018, September). Table 3. Electronically mediated workers by selected characteristics, in thousands, May 2017 [Data file]. Retrieved from https://www.bls.gov/cps/electronically-mediated-employment.htm

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Similarly, the normal distribution hypothesis is confirmed for Electronically mediated workers - the observed Pearson statistics was 4.36, which is less than the critical, the distribution parameters are h_{μ}=4.64 and σ_h=1.69.

At the same time, distribution is not normal for contingent workers and workers with alternative working conditions according to the Pearson agreement criterion. However, additional verification showed that a lognormal distribution law is suitable for these employment types, since the share logarithms are normally distributed.

Figure 1 shows the empirical (black histogram) and theoretical (red curve) distributions for a) noncontingent workers/workers with traditional work arrangement; b) contingent workers; c) workers with alternative work arrangement; d) electronically mediated workers.

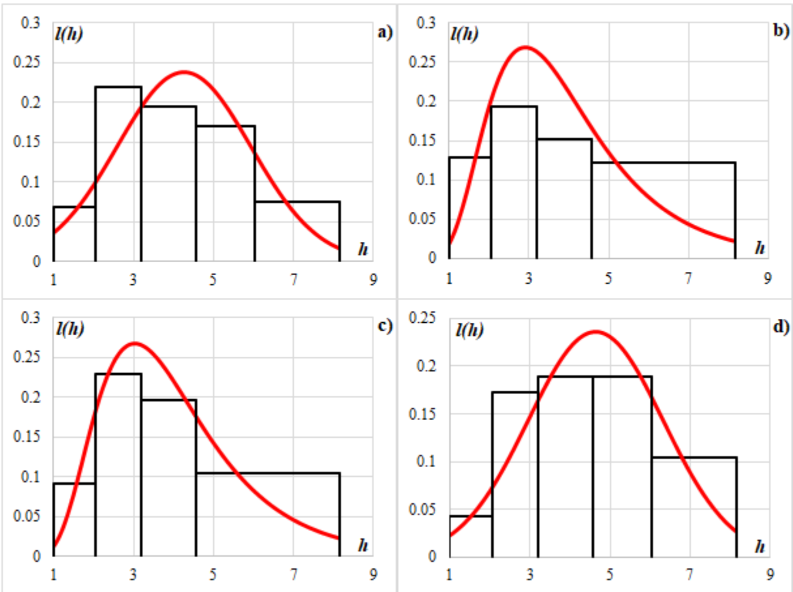

Figure 1. Empirical and theoretical distribution of relative labor force by skill level

Based on the obtained theoretical distributions, taking into account the functional transformation given by formula (4), using formula (6), we calculated the change in the employed effective labor shares in the U.S. economy as a result of digital transformation (Table 2).

Table 2. Low, medium and high skilled workers shares with employment traditional type before and after digital transformation

Before digital transformation	$\lambda_{ef}^{(l)}$=10.5%	$\lambda_{ef}^{(m)}$=72.4%	$\lambda_{ef}^{(h)}$=17.2%
After digital transformation	$\lambda_{efe}^{(l)}$=24.3%	$\lambda_{efe}^{(m)}$=49.2%	$\lambda_{efe}^{(h)}$=26.5%

According to calculations using formula (4), digital transformation will lead to 51% of workforce replacement of medium and high qualifications with employment traditional type. Taking into account the distributions characteristics - the contingent labor force average human capital according to formula (1) is 3.83, and for workers with alternative working conditions it is 3.85 - according to calculations using the model, the most likely scenario is in which 19.5% of replaced labor resources will be forced to abandon traditional employment in favor of other types. Thus, if according to U.S. Federal Bureau of Labor Statistics in 2017, 87.1% of workers with traditional employment were observed in the employed structure, then as a result of digital transformation, this share will decrease to 67.6%. In this scenario, replacing labor process with intelligent machines will lead to an increase in electronically mediated workers number by 26%.

7. Conclusion

The 2020s will see a steady technological shift in labor demand towards high qualifications. According to our estimates, in the 2030s in U.S. economy the highly skilled workers share with a master's degree and above will be 26.5% of employed in labor force economy, against the current 17.2%. Also, in the course of digital transformation, there will be a significant polarization of labor into highly- and low-skilled, with a sharp reduction in jobs of average qualifications - the workers share with average qualifications will decrease to 49.2%, from the current 72.4%.

As a result of workforce replacement with I.M., the employed on electronic platforms share will grow by 26%, and contingent workers and workers with alternative working conditions will account for about third of all employed in labor market.

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