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Assessment of the Impact of the Digital Economy on Labor Resources Transformation in Kazakhstan

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ABSTRACT

The present paper analyzed the impact of the digital economy and innovations on Kazakhstan's labor resource transformation from theoretical and empirical perspectives. By means of correlation analysis the factors that were the most significant for the result variable - the employed population in high-tech and knowledge-intensive sectors of the economy were determined (R2>0,8). However, the correlation analysis revealed the multicollinearity - close linear relationship between all factors. In this regard, the method of statistical equations of dependencies was applied for further research. During the study, a multifactorial equation of dependencies was calculated. Key socio-economic factors influencing population employment in high-tech and knowledge-intensive sectors of the economy were determined. The degree of influence of each factor on the result variable was calculated. Thus, the level of employment in high-tech and knowledge-intensive industries of Kazakhstan is most influenced by four key factors: the share of Internet users, the degree of influence of this indicator is the most significant and amounted to 38.28%; the share of computer users – 28.27%; gross domestic product per capita - 19.47%; and internal expenditure on research and development work – 11.69%. Taking into account the fact that the digital innovation era today is almost at the very beginning of its development, the digital processes occurring in the economy, in particular in the labor market, require monitoring and in-depth analysis for the timely development of management levers and control of their impact, that only emphasizes the relevance of this study.

KEYWORDS: Economy, Digital Economy, Digitalization, Social Economy, Human Capital, Labor Resource, Employment, Transformation

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Оценка влияния цифровой экономики на трансформацию трудовых ресурсов в Казахстане

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АННОТАЦИЯ

В данной статье было изучено влияние цифровой экономики и инноваций на трансформацию трудовых ресурсов Казахстана как с теоретической, так и с эмпирической точек зрения. Посредством корреляционного анализа были выделены те факторы, которые оказались наиболее значимы для результативного фактора - занятого населения в высокотехнологичных и наукоёмких отраслях экономики ($R2>0,8$). Однако при проверке на мультиколлинеарность корреляционная таблица показала тесную линейную связь между всеми факторами. В связи с чем, авторами было решено использовать метод статистических уравнений зависимостей. В ходе исследования рассчитано многофакторное уравнение зависимостей, определены ключевые социально-экономические факторы, оказывающие влияние на занятость в высокотехнологичных и наукоёмких отраслях, а также произведён расчёт степени влияния каждого из факторов на результативный признак. Так, на уровень занятости населения в высокотехнологичных и наукоёмких отраслях Казахстана наибольшее влияние оказывают четыре ключевых фактора: доля пользователей сети Интернет, степень влияния этого показателя наиболее значимая и составила 38,28%; доля пользователей компьютеров – 28,27%; валовый внутренний продукт на душу населения – 19,47% и внутренние затраты на научно-исследовательские и опытно-конструкторские работы – 11,69%. Учитывая тот факт, что цифровая инновационная эра сегодня находится практически в самом начале своего развития, то цифровые процессы, происходящие в экономике, в частности на рынке труда, требуют мониторинга и глубокого анализа для своевременной разработки рычагов управления и контроля их влияния, что только подчёркивает актуальность настоящего исследования.

КЛЮЧЕВЫЕ СЛОВА: экономика, цифровая экономика, цифровизация, социальная экономика, человеческий капитал, трудовые ресурсы, занятость, трансформация

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INTRODUCTION

In recent decades, the development of the global digital economy has taken an important position and has shown rapid growth (Chen et al., 2022). The digital economy in Kazakhstan is recognized as a key priority in the country's development agenda. In 2017, the government launched the "Digital Kazakhstan" program, designed to enhance the efficiency of public administration, foster business development, and improve its citizens' overall quality of life (Bashieva et al., 2023). Moreover, in March 2023, the Government of the Republic of Kazakhstan approved the "Concept of Digital Transformation, Development of the Information and Communication Technologies Industry, and Cybersecurity for 2023-2029" through a Government Resolution, marking a significant step in the nation's digitalization efforts.

The digital economy transition significantly impacts the labor market due to the large-scale transformation of requirements for specialists and increased labor market efficiency. Digital technologies implementation automates many operations of labor activity, which leads to significant changes in the needs and requirements for labor resources, as well as creates efficient and fast job search, including the possibility of remote work activity (Chebakova & Knyazeva, 2024).

In the present paper, we attempt to assess labor resource transformation in terms of innovation and the digital economy. To this end, the share of employment in high-tech and knowledge-intensive sectors of the economy, which includes industries where digital technologies are an essential component - such as manufacturing, information and communication, and professional, scientific, and technical activities - were selected as a result variable characterizing this transformation.

Subsequently, the study explores the stable relationships between the result variable -employment in high-tech and knowledge-intensive sectors of the economy - and several independent variables - factors that reflect the ongoing transformation of the labor market. Thus, as independent variables were selected, the following indicators: gross coverage of higher education, the population in cities, the unemployment rate, the average monthly nominal wage, gross domestic product per capita, the balance of external migration of the population, the share of Internet users, the share of computer users, the level of activity of enterprises in the field of innovation, internal R&D expenditures.

The purpose of this study was to identify a stable relationship between the result and independent variables, as well as to calculate the degree of influence of each of the independent variables (factors) on employment in high-tech and knowledge-intensive sectors of the economy (result variable).

The future research agenda involves a comprehensive analysis of long-term trends in the evolution of labor market structure and employment patterns. Such an investigation would enable more precise forecasting of the impact of digital technologies on the national economy. Furthermore, it would provide a foundation for developing informed recommendations to enhance state support mechanisms for innovation-driven sectors and cultivate a skilled workforce in the context of emerging digital transformations.

All calculations conducted during the present research paper are grounded in statistical data supplied by the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan.

LITERATURE REVIEW

There is some conflicting data in the scientific literature regarding the impact of digitalization on the labor market transformation. US researchers have noted that one of the indicators that digitalization is affecting the social structure is the sharp decline in the share of labor in US national income, which is a consequence of the transformation of society under the influence of digital intelligence (Karabarbounis & Neiman, 2014; Oberfield & Raval, 2021). As digitalization and artificial intelligence become more pervasive in people's lives, new technologies may reduce the need for human resources in the labor market (Graetz & Michaels, 2018; Acemoglu & Restrepo, 2018).

At the same time, according to some scholars, digitalization not only contributes to the productivity of individual enterprises but also creates opportunities for the accumulation of long-term capital and deepening automation processes, which in turn leads to increased demand for labor in other sectors of the economy and creates new employment opportunities (Acemoglu и Restrepo, 2019).

Moreover, with the development of digital transformation, the very concept of "employment" has transformed from static and constant to flexible, from traditional to evolving, and from professional to complex (Bolt et al., 2022).

A literature review on the topic of the study revealed that existing studies on analyzing the impact of digital transformation on the workforce often focus on macro-level analysis. There is a logical explanation for this fact: as many researchers note, the issue of transformation is new and relevant but remains completely unexplored for several reasons, one of which is the small volume of empirical research at the company level (Chen & Srinivasan, 2023). Even though theoretical research on digitalization and the labor market exists, empirical evidence on the impact of digital technologies on the labor force, especially at the level of individual companies, is very limited (Autor & Dorn, 2013).

Moreover, digitalization affects technological changes and social, cultural, and organizational processes. This creates difficulties in accurately modeling the relationship between technological innovations and changes in the labor market (Gaggl & Wright, 2017). Therefore, forecasting this kind of process requires considering many factors, such as legislative changes, global economic trends, and the speed of implementation of new technologies (Wilson & Daugherty, 2018).

Digitalization also leads to changes in employment patterns, such as increased freelancers working remotely or a shift to short-term contracts (Brynjolfsson & McAfee, 2016). These changes often occur at the micro level, making it difficult to collect and process the data needed to understand the impact of digital technologies on labor markets as a whole (Qin et al., 2024).

Furthermore, the transition to remote work and short-term contracts necessitates rethinking vocational training and requalification approaches, as these employment forms demand specific skills, such as self-organization, high mobility, and adaptability to rapidly changing environments. Since these shifts in labor relations are often not reflected in traditional data sources, an essential area for future research lies in developing new methodologies for collecting and analyzing data that will enable a more precise evaluation of the impact of digitalization on the labor market and its structure.

An equally important reason is the lack of statistical data. To establish the cause-and-effect relationships of labor transformation, detailed data are needed, the lack of which makes it challenging to study the impact of digital transformation on specific segments of the labor market, especially in rapidly changing industries such as IT, artificial intelligence, robotization, and other high-tech areas. In countries where digitalization is just beginning to develop, collecting such data is complex and not consistently sufficiently accurate, and Kazakhstan is no exception in this matter. For instance, observations on some indicators characterizing the population's digital literacy level have been conducted only since 2018, which certainly is insufficient for building an econometric model and, even more so, forecasting.

METHODS OF THE RESEARCH

This study used several statistical methods to analyze the factors influencing employment in high-tech and knowledge-intensive sectors of the economy, aimed at identifying stable dependence of the result and independent variables.

In the first stage of the study, correlation diagnostics were carried out to identify statistical relationships between different variables. For this purpose, the correlation coefficient was used to measure the strength and direction of the linear relationship between factors such as the share of Internet users, the share of computer users, gross domestic product per capita, domestic expenditures on R&D, and the level of employment in high-tech and knowledge-intensive sectors of the economy.

Correlation analysis allowed us to establish a primary relationship between variables, which became the starting point for further calculations. However, the analysis revealed the presence of multicollinearity - a situation when factors are highly correlated, leading to distortion of regression analysis results and misinterpretation of model parameters.

The method of statistical equations of dependencies was used to take into account multicollinearity and correctly analyze the factors affecting employment in high-tech and knowledge-intensive sectors of the economy. When applying the method of statistical equations of dependencies, it is essential to exclude outliers, particularly extreme values of independent variables (minimum or maximum) that deviate substantially from the next closest value while ensuring the stability of relationships between the dependent and independent variables (Rakhmetova & Dubrova, 2011).

This method is a system of linear or nonlinear equations in which one or more variables depend on others. This study considered the linear multifactorial dependence of employment in high-tech and knowledge-intensive industries on 10 indicators from different blocks of statistical data of the republic.

Then, using the formulas of the statistical equation, the linear multifactorial dependence of sustainable growth of employment in high-tech and knowledge-intensive sectors of the economy on ten factors (independent variables) over the past 16 years was considered by formulas (1) and (2):

$$y_x = y_{min} (1 + b\ d_{(xi / xmin - 1)}) \quad (1)$$

$$y_x = y_{min} (1 + b\ d_{(1 - xi / xmax)}) \quad (2)$$

where:

y_x – result variable

y_{min} – minimum value of the result variable

b – ratio of the sum of deviations from the unit of the calculated coefficients of comparison of the result and independent factors

d_{xi} – comparison coefficient of the independent factor as a whole

$d_{x(min)}$ – comparison coefficient to the minimum value of the independent factor

$d_{x(max)}$ – comparison coefficient to the maximum value of the independent factor

For further research and calculation, the equation of multifactor dependence was applied. The parameters of the equation are calculated following formula (3):

$$y^* = y_{min}(1+B(d_{x3} + d_{x6} + d_{x8} + d_{x9} + d_{x10})) \quad (3)$$

where:

$d_{x3}=x_3/x_{3min}-1$,

$d_{x6}= x_6/x_{6min}-1$,

$d_{x8}= x_8/x_{8min}-1$,

$d_{x9}= x_9/x_{9min}-1$,

$d_{x10}= x_{10}/x_{10min}-1$,

$d_y=y_i/y_{min}-1$

Having calculated the parameters of the equation of multifactor dependence, we further calculated the change in the size of deviations of the comparison coefficients of the result variable when the aggregate size of deviations of the comparison coefficients of the independent variables x3-10 (all factors) changes by one according to formula 4.

$$B = \sum dy/(\sum dx3 + \sum dx6 + \sum dx8 + \sum dx9 + \sum dx10) \quad (4)$$

Finally, formula 5 determined the degree of influence of each factor on the population employment in high-tech and knowledge-intensive sectors of the economy.

$$\Delta_{xi} = (\frac{\sum d_{xi}}{\sum d_{xij}})x100\% \quad (5)$$

Where:

Δ_{xi} - share of influence of a single factor on the result variable;

$\sum d_{xi}$ - the sum of deviations of comparison coefficients of a single factor;

$\sum d_{xij}$ - the sum of the deviations of the comparison coefficients of all factors.

To verify the adequacy of the obtained linear equations of dependence, calculations of parameters and stability of the relationship between the result variable and each independent factor separately were carried out, where the correlation coefficient with different independent factors ranged from 0.95 to 0.99, and the stability coefficient was not less than 0.8, which once again proved the strong relationship between the factors and complete fulfillment of the requirement to assess the correctness of the calculation.

RESULTS

The Bureau of National Statistics of the Republic of Kazakhstan regularly provides statistical data, and to assess the impact on the transformation of labor resources, we have revealed statistical indicators that reflect changes in the structure, composition, qualifications, and distribution of the labor force. Labor resources transformation is associated with adapting the labor force to changes in the economy, technology, social environment, and political situation. Thus, for econometric modeling and forecasting, as a result, variable, this research defined the employment of the population in high-tech and knowledge-intensive sectors of the economy, including the employed population in industry, information, and communication, as well as professional, scientific, and technical activities (X1).

This choice is determined by the fact that the above-mentioned sectors of the economy have the most significant impact on digital technologies. High-tech and knowledge-intensive industries play a key role in economic growth and technological progress since they create new products and services, as well as implement innovative projects that require the use of the most advanced digital technologies. The employment indicator for high-tech and knowledge-intensive industries provides the most accurate picture of the impact of digitalization on the labor market, how it contributes to the creation of new jobs, and how the skills requirements of employees are changing. This provides an insight into how the transition to a digital economy affects the labor force, its structure, and the skills in demand.

Furthermore, due to their specifics, high-tech and knowledge-intensive sectors actively influence structural changes in other sectors of the economy. Implementing digital technologies and innovations leads to increased labor productivity and improved quality of work, which, in turn, causes labor resource transformation in related industries such as education, health care, transport, and others. Thus, employment in these sectors indicates broader processes taking place in the labor market, such as shifting skill profiles required for successful integration into the digital economy.

The following factors were selected as independent variables:

X2 - Gross higher education enrollment, %;

X3 - Population in cities, people;

X4 - Unemployment rate, %;

X5 - Average monthly nominal wage, tenge

X6 - Gross domestic product per capita, tenge;

X7 - Balance of external migration of the population;

X8 - Share of Internet users aged 6 to 74, %;

X9 - Share of computer users aged 16-74, %;

X10 - Internal R&D expenditure, million tenge.

X11 - Level of enterprises' activity in the innovation field, %.

The choice of these factors as independent variables in econometric modeling to evaluate the impact of the digital economy on the transformation of labor resources is based on their strong connection to the primary processes occurring within digitalization and innovation-driven economic development. These factors encompass essential elements that directly or indirectly influence the labor market, employment levels, and the workforce's skillset amid the digital transformation.

Gross higher education enrolment (X2) is a crucial indicator, as higher levels of education are closely tied to the labor force's ability to adapt to the digital economy's demands. The digitalization of the economy requires highly skilled professionals who can work with modern technologies. The higher the educational attainment, the more likely the workforce is to meet the demands of digital technologies. This factor reflects the population's capacity to integrate into high-tech industries and their readiness to learn and develop in response to rapid technological advancements.

Digital economy development is associated with the population concentration in urban centers where technology startups, innovative companies, and research institutions are concentrated. Therefore, the population in cities (X3) is also a significant indicator. The urban setting enhances the availability of employment opportunities within advanced technological sectors, simultaneously expediting the diffusion of emerging technologies and digital innovations across the economic landscape. The progressive intensification of urbanization cultivates a conducive environment for the robust expansion of the digital economy, while fostering the development of infrastructure that supports employment within cutting-edge and digitally-driven industries.

In the context of the digital economy, the unemployment rate (X4) is another crucial indicator since digitalization often leads to structural changes in the labor market. Implementation of new technologies can both reduce the need for certain professions and create new work positions. However, successful labor resource adjustment to new conditions requires retraining and upskilling the employees, affecting the unemployment rate. Understanding unemployment dynamics helps determine how effectively labor resources adapt to the changes generated by the digital economy.

Average monthly nominal wages (X5) serve as a significant indicator of the economic appeal of high-tech and knowledge-intensive sectors, which are pivotal sources of job creation in the digitalization context. Wage growth within these industries typically correlates with increased employee qualifications and the emergence of new professions associated with digital technologies. Rising wages in these sectors may signal a transformation in the labor market, wherein skilled professionals become increasingly valuable and in demand.

Gross Domestic Product per capita (X6) is a fundamental indicator that reflects the overall economic development of a country, including within the framework of the digital economy. The growth of GDP per capita, fueled by the expansion of high-tech and innovative sectors, directly influences employment levels within these industries. The progression of the digital economy drives enhancements in labor productivity and optimizes economic performance, thereby facilitating new employment opportunities and elevating the quality of workforce participation.

Gross domestic product per capita (X6) is a fundamental indicator that reflects the overall economic development of a country, including within the framework of the digital economy. The growth of GDP per capita, fueled by the expansion of high-tech and innovative sectors, directly influences employment levels within these industries.

The share of Internet users (X8) and computer users (X9) directly measures the level of digital literacy and the accessibility of technologies within the population. The higher these indicators, the more prepared the population is to meet the digital economy's demands, fostering more significant employment in high-tech and knowledge-intensive industries. These factors are critical markers of the population's engagement with the digital environment and readiness to incorporate new technologies into their professional activities.

Internal R&D expenditure (X10) and the level of innovation activity of enterprises (X11) are critical factors that reflect the intensity of innovation development and the extent to which companies are engaged in the digitalization process. Corporate innovation activity is closely linked to developing new technologies, which generates new opportunities for highly qualified labor. R&D expenditure, in turn, signifies the degree to which enterprises allocate resources to research and innovation, directly influencing job creation and altering the employment structure within high-tech industries.

The above-mentioned factors were selected as independent variables in the econometric modeling because they provide a comprehensive representation of critical aspects of the digitalization process within the economy. This includes factors such as educational attainment, access to technology, innovation dynamics, and economic development, all of which influence workforce transformation. They offer valuable insights into how the digital economy affects employment and the labor market, the evolving skill requirements, and the emerging opportunities for workers.

Correlation analysis was carried out to determine whether there is a relationship between the result and independent variables (Table 1).

Table 1. Correlation of population employment in high-tech and knowledge-intensive sectors of the economy and factor indicators (independent variables)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
x1	1										
x2	0,61	1									
x3	0,91	0,65	1								
x4	-0,90	-0,53	-0,77	1							
x5	0,82	0,57	0,97	-0,67	1						
x6	0,88	0,64	0,99	-0,74	0,99	1					
x7	-0,66	-0,62	-0,40	0,58	-0,21	-0,33	1				
x8	0,96	0,61	0,87	-0,96	0,78	0,84	-0,61	1			
x9	0,95	0,59	0,86	-0,96	0,77	0,83	-0,60	0,99	1		
x10	0,98	0,72	0,92	-0,88	0,83	0,89	-0,66	0,94	0,92	1	
x11	0,81	0,46	0,94	-0,66	0,98	0,96	-0,16	0,77	0,75	0,80	1

Note: compiled by authors

According to Table 1, a strong correlation between employment in high-tech and knowledge-intensive sectors of the economy (correlation coefficient greater than 0.8) is observed with 8 out of 10 factors (independent variables), including:

X3 - Population in cities, people;

X4 - Unemployment rate, %;

X5 - Average monthly nominal wage, tenge

X6 - Gross domestic product per capita, tenge;

X8 - Share of Internet users aged 6 to 74, %;

X9 - Share of computer users aged 16-74, %;

X10 - Internal R&D expenditure, million tenge.

X11 - Level of enterprises' activity in the innovation field, %.

At the same time, the correlation calculation of the dependence of population employment in high-tech and knowledge-intensive sectors of the economy on independent variables showed multicollinearity, i.e., a strong relationship is observed not only between the result variable and independent variables but also between independent variables themselves.

Given the multicollinearity of factors and the limited sample size (16 observations) spanning from 2008 to 2023, the analysis proceeded with the application of the method of statistical dependency equations. Unlike traditional regression analysis, this method facilitates modeling direct and indirect relationships between variables, which is particularly advantageous when multicollinearity is present. Furthermore, this approach provides a more adaptable framework for modeling dependencies, thus rendering it more robust to issues arising from multicollinearity. Consequently, it contributes to the estimates' stability and enhances the model's predictive precision.

Then, using the formulas of the statistical equation, the linear multifactorial dependence of sustainable growth of employment in high-tech and knowledge-intensive sectors of the economy on ten factors (independent variables) over the past 16 years was considered.

Before establishing multifactor dependence, the stable dependence of employment growth in high-tech and knowledge-intensive sectors of the economy on each of the ten factors will be determined. Using the formulas of the single-factor dependence equation, the coefficient of stable dependence will be calculated (К).

The calculation with other factors (independent variables) will be done analogically. For illustrative purposes, Table 2 shows the calculation of parameters and stability of the relationship between employment in high-tech and knowledge-intensive sectors of the economy (Y) and independent variable X10.

Table 2. Calculation of parameters and stability of the dependence between employment in high-tech sectors (Y) and variable X10

Year	Y	X10	dy	dx	вdx	У*	dx*dy	dx2	dy2	dy-bdx
2008	1187,5	4,0	0	0	0	1187,5	0	0	0	0
2009	1196	4,0	0,0071579	0	0	1187,5	0	0	5,1235E-05	0,007158
2010	1207,4	4,3	0,0167579	0,075	0,01283334	1202,73959	0,001257	0,005625	0,00028083	0,003925
2011	1265,4	5,7	0,0656	0,425	0,07272227	1273,8577	0,02788	0,180625	0,00430336	0,007122
2012	1320,014	5,7	0,1115907	0,425	0,07272227	1273,8577	0,047426	0,180625	0,01245249	0,038868
2013	1354,284	8,0	0,1404497	1	0,17111123	1390,69459	0,14045	1	0,01972611	0,030662
2014	1412,748	8,1	0,1896825	1,025	0,17538901	1395,77445	0,194425	1,050625	0,03597946	0,014294
2015	1456,681	8,1	0,2266787	1,025	0,17538901	1395,77445	0,232346	1,050625	0,05138325	0,05129
2016	1487,512	9,3	0,2526417	1,325	0,22672238	1456,73283	0,33475	1,755625	0,06382782	0,025919
2017	1485,678	9,6	0,2510973	1,4	0,23955572	1471,97242	0,351536	1,96	0,06304984	0,011542
2018	1513,162	10,6	0,2742417	1,65	0,28233353	1522,77107	0,452499	2,7225	0,0752085	0,008092
2019	1513,008	11,3	0,274112	1,825	0,31227799	1558,33012	0,500254	3,330625	0,07513739	0,038166
2020	1503,544	11,5	0,2661423	1,875	0,32083356	1568,48985	0,499017	3,515625	0,07083173	0,054691
2021	1506,925	10,5	0,2689895	1,625	0,27805575	1517,6912	0,437108	2,640625	0,07235534	0,009066
2022	1541,276	11,0	0,2979166	1,75	0,29944465	1543,09052	0,521354	3,0625	0,08875432	0,001528
2023	1574,294	11,7	0,3257213	1,925	0,32938912	1578,64958	0,627013	3,705625	0,10609434	0,003668
	22525,43	133,4	2,9687798	17,35		22525,4261	4,367315	26,16125	0,73943602	0,30599
	B =	0,17111	r	19,344	0,9929673	K	0,896931			

Note: compiled by authors

Table 2 illustrates a stable relationship between employment in high-tech and knowledge-intensive industries and the independent variable X10 - Internal R&D expenditure. The stability coefficient was equal to 0.89. The calculation of the other factors will be carried out in the same way.

Thus, the results represent that a high coefficient of stability is observed in population employment in high-tech and knowledge-intensive sectors of the economy from the following five indicators: the number of populations in cities (X3), gross domestic product per capita (X6), the share of Internet users (X8), the share of computer users (X9) and internal expenditure on R&D (X10). Calculations show that factors X2, X4, X5, X7, and X11 do not have a stable relationship with the result variable (coefficient less than 0.7).

Using the calculation results, one-factor equations of dependencies of population employment in high-tech and knowledge-intensive sectors of the economy with each factor (independent variables) will be complied with in Table 3.

Table 3. Equations of one-factor dependence

Factor		Equation	К
X3	Population in cities	У= 1187,50 (1+0,8761*dx3)	0,807
X6	Gross domestic product per capita	У=1187,50 (1+0,1027*dx6)	0,896
X8	Share of Internet users	У=1187,50 (1+0,5225*dx8)	0,857
X9	Share of computer users	У=1187,50 (1+0,0707*dx9)	0,844
X10	Internal expenditure on R&D	У=1187,50 (1+1,1711*dx10)	0,896

Note: compiled by authors

Table 3 compiled by authors on the basis of the results of calculations of parameters and stability of the relationship between population employment in high-tech and knowledge-intensive sectors of the economy and independent variables (factors). Thus, the table presents five single-factor equations illustrating the dependence of employment in high-tech and knowledge-intensive industries on five selected factors. The strongest stable relationship between the result variable and independent variables is observed with two variables: gross domestic product per capita (X6) and internal R&D expenditure (X10), with a coefficient of 0.896. The stable relationship with other independent variables is slightly lower, with a coefficient of 0.857 for the share of Internet users (X8), 0.844 for the share of computer users (X9), and 0.807 for the population in cities (X3).

Subsequently, the calculation of the multifactor combinatorial dependence equation. The calculation of the parameters for the multifactor equation is provided in Table 4.

Table 4. Calculation of parameters of the equation of multifactor dependence

Year	dx3	dx6	dx8	dx9	dx10	dx3+dx6+dx8+dx9+dx10	dy	bdx	Y*
2008	0	0	0	0	0,0000	0,0000	0,0000	0,0000	1187,50
2009	0,0480	0,0319	0,2053	0,0374	0,0000	0,3227	0,0072	0,0065	1196,00
2010	0,0670	0,3050	1,0938	1,3369	0,0750	2,8777	0,0168	0,0576	1207,40
2011	0,0857	0,6655	2,2788	1,5348	0,4250	4,9897	0,0656	0,0998	1265,40
2012	0,1042	0,8034	3,4967	2,5882	0,4250	7,4176	0,1116	0,1484	1320,01
2013	0,1224	1,0633	3,4768	2,5241	1,0000	8,1866	0,1404	0,1638	1354,28
2014	0,1413	1,2408	3,5099	2,5561	1,0250	8,4731	0,1897	0,1695	1412,75
2015	0,1901	1,2755	4,1126	3,1283	1,0250	9,7315	0,2267	0,1947	1456,68
2016	0,2141	1,5774	4,3113	3,2086	1,3250	10,6363	0,2526	0,2128	1487,51
2017	0,2499	1,9436	4,3974	3,2406	1,4000	11,2314	0,2511	0,2247	1485,68
2018	0,2715	2,3026	4,5232	3,3422	1,6500	12,0895	0,2742	0,2419	1513,16
2019	0,2943	2,6671	4,7351	3,4118	1,8250	12,9332	0,2741	0,2588	1513,01
2020	0,3233	2,6779	4,8940	3,5775	1,8750	13,3478	0,2661	0,2671	1503,54
2021	0,3491	3,3140	5,1788	3,7647	1,6250	14,2316	0,2690	0,2847	1506,93
2022	0,4507	4,1600	5,2583	3,8235	1,7500	15,4425	0,2979	0,3090	1541,28
2023	0,4771	4,8604	5,3444	3,8663	1,9250	16,4732	0,3257	0,3296	1574,29
Total	3,3886	28,8884	56,8163	41,9412	17,3500	148,3844	2,9688	2,9688	22525,43

Note: compiled by authors

Table 4 represents the parameters of the equation of multifactor dependence. Using these parameters, we calculated how the change in the total size of deviations of the comparison coefficients of independent variables X3, X6, X8, X9, X10 per unit causes a change in the size of deviations of the comparison coefficients of the employment in high-tech and knowledge-intensive industries (Y).

$$B = \sum dy / (\sum dx3 + \sum dx6 + \sum dx8 + \sum dx9 + \sum dx10) = \frac{2,9688}{148,3844} = 0,020007$$

Thus, a change in the total size of deviations of the comparison coefficients of all independent variables X3, X6, X8, X9, X10 per unit causes a change in the size of deviations of the comparison coefficients of the employment in high-tech and knowledge-intensive industries (Y - result variable) by 0.020007 times.

Next, using formula 5, the percentage of influence of each factor on the population employment in high-tech and knowledge-intensive sectors of the economy will be determined (Table 5).

Table 5. The share of influence of individual factors on employment in high-tech and knowledge-intensive sectors of the economy

No.	Factor	Share of influence of the factor, %	Ranking
1	X3 - Population in cities	2,28	5
2	X6 - Gross domestic product per capita	19,47	3
3	X8 -Share of Internet users	38,29	1
4	X9 - Share of computer users	28,27	2
5	X10 - Internal expenditure on R&D	11,69	4
	Total	100	-

Note: compiled by authors

Based on the data presented in Table 5, it is evident that the greatest impact on employment in high-tech and knowledge-intensive industries is exerted by the share of Internet users, with an influence of 38.29%. The second most significant factor is the share of computer users, accounting for 28.27%. The third largest influence is Gross Domestic Product per capita, with an impact of 19.47%. Domestic expenditure on R&D also plays a notable role in shaping employment in these sectors, with an influence of 11.69%. The factor with the smallest impact among the five is the population in cities, contributing only 2.28% to employment in high-tech and knowledge-intensive industries.

CONCLUSION

The present research demonstrates the significant impact of the digital economy and innovation processes on the transformation of labor resources in Kazakhstan. The work has analyzed both theoretical and empirical aspects of this process, revealing key socio-economic factors that determine the level of employment in high-tech and knowledge-intensive sectors of the economy.

Thus, among the considered socio-economic indicators, provided by the Bureau of National Statistics, which in one way or another could have an impact on employment in high-tech and knowledge-intensive sectors of the economy, the conducted correlation analysis identified 8 factors that have the strongest relationship with the result variable (Bureau of National Statistics, 2024). However, due to the close linear relationship of variables among themselves, further research was conducted using the statistical equations of dependence, requiring the absence of multicollinearity of variables.

According to the calculations performed using the above-mentioned method, 4 key factors that have a fundamental impact on the growth of employment in high-tech and knowledge-intensive sectors of the economy were revealed, and the influence percentage of each factor was also calculated.

The findings of the study indicate that, in the context of the growing digitalization of the economy, the accessibility of technologies and their incorporation into production processes are crucial factors influencing the employment of highly skilled professionals, mainly within high-tech and knowledge-intensive sectors. Despite the initial stage of digital transformation in Kazakhstan, it is obvious that digital processes have a serious impact on the labor market, which requires constant monitoring and accurate analysis for timely response to changes and adjustments in public policy.

Furthermore, there is a pressing need to enhance the role of state support for research and development of emerging technologies, which would facilitate the advancement of digital infrastructure and promote job creation within innovation-driven sectors. Establishing an environment conducive to increased innovation and boosting domestic expenditure on R&D could serve as pivotal catalysts for employment growth in high-tech and knowledge-intensive sectors of the economy.

Additionally, within the scope of digital transformation, it is crucial to account for the rapid expansion of flexible employment models, such as freelancing and remote work. This necessitates a fundamental reassessment of regulatory frameworks governing labor relations, alongside the development of robust legal and economic mechanisms designed to safeguard workers' rights and ensure that labor legislation is adapted to the evolving demands of the digital economy.

In light of these developments, a key area for future research will involve analyzing the dynamics of these transformations and forecasting their long-term implications for the labor market. The establishment of effective data collection and analysis methodologies and the formulation of predictive tools and mechanisms for assessing the real-time impact of digitalization on employment will be essential for the optimal regulation and adjustment of labor and employment policies within the digital economy.

AUTHOR CONTRIBUTIONS

Conceptualization and theory: SK, AM, RR and AS; research design: SK; data collection: SK and AM; analysis and interpretation: SK and AS; writing draft preparation: SK, AM and RR; supervision: SK, AM and RR; correction of article: SK and AS; proofread and final approval of article: SK, AM, RR and AS. All authors have read and agreed to the published version of the manuscript.

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