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E. V. Prushkivska[1],
orcid.org/0000-0002-4227-8305,
Y. I. Pylypenko[*2],
orcid.org/0000-0002-4772-1492,
A. M. Tkachuk[2],
orcid.org/0009-0005-3061-282X,
H. M. Pylypenko[2],
orcid.org/0000-0003-2091-4320,
V. O. Los[3],
orcid.org/0000-0002-7932-5232

1 – The National University of Life and Environmental Sciences of Ukraine, Kyiv, Ukraine
2 – Dnipro University of Technology, Dnipro, Ukraine
3 – Kyiv Metropolitan Institute named after Borys Grinchenko, Kyiv, Ukraine
[*] Corresponding author e-mail: pylypenkoyi@gmail.com

POST-INDUSTRIAL TRANSFORMATIONS OF SOCIETY AND THEIR IMPACT ON THE EMPLOYMENT STRUCTURE

Purpose. To clarify the essence and consequences of digital transformation of employment in the context of post-industrial transformations, to identify key factors influencing the structure, forms, and dynamics of employment in the digital economy, and to subsequently develop a methodological approach to analyzing these changes based on cognitive modeling.

Methodology. The study uses cognitive modeling as an interdisciplinary tool for analyzing the transformation of employment in the digital economy. The methodological basis is a systematic approach to identifying and formalizing complex cause-and-effect relationships between economic, technological, socio-demographic, and institutional factors that determine changes in the structure of the labor market. The modeling process uses an expert analytical knowledge base that provides a representative reflection of current transformation trends, in particular the dynamics of the formation of new forms of employment (gig economy, remote work) and the gradual reduction of traditional forms of labor participation. This approach allows for the effective study of insufficiently structured or poorly formalized processes characteristic of rapid digitalization.

Findings. A cognitive model of employment transformation has been developed, which visualizes the interrelationships between the main factors of digitalization and structural changes in the labor market. The key influences of technological progress on changes in labor demand, professional mobility, the dynamics of the emergence of new professions, and the transformation of labor relations have been identified. The model allows forming scenarios for the development of employment in the digital economy and adapt labor market policies to new challenges.

Originality. The feasibility of using cognitive modeling as a tool for studying employment transformation is substantiated, which provides a deeper understanding of structural changes in the labor market in the context of digitalization. A conceptual model has been developed that combines technological, social and economic aspects of post-industrial changes and allows predicting their impact on employment, identifying hidden relationships and creating a basis for making strategic management decisions.

Practical value. The results of the study can be used to improve employment management strategies in the context of the digital transformation of the economy. The proposed cognitive model of the digital transformation of employment allows us to identify key factors that determine the dynamics of changes in the structure of the labor market. Along with this, it can be used to assess the risks and potential of automation in various sectors of the economy, to model employment development scenarios depending on the level of digitalization. The practical application of the results of cognitive modeling will allow us to form more effective employment policy directions that can ensure flexibility, social sustainability and competitiveness of the national labor market in the long term.

Keywords: *digitalization, post-industrial transformation, employment, employment structure, labor market, cognitive modeling*

Introduction. The modern world is undergoing post-industrial transformations that began in the 1970s and are now clearly demonstrating the emergence of a fundamentally new society. Its main feature is the transition from an industrial economy to an economy based on knowledge and information. The driving force behind the development of such a society is breakthrough technologies that revolutionize production, open up new ways of increasing labor productivity, generate new organizational forms, and change the social and institutional landscape. All these technologies have one key feature in common: they use the power of digitalization and information technology [1]. The latter not only radically change the ways in which production and management models function, but also transform the very nature of employment.

Intensive implementation of digital technologies, such as automation, artificial intelligence, machine learning, big data processing platforms, cause a structural restructuring of the labor market. This is manifested in the decline of traditional forms of work and the emergence of new formats of employment. The latter require employees with a high level of digital competence who are capable of continuous learning, possess flexibility, cross-functionality, and the ability to adapt to technological changes. The labor market increasingly differentiates workers not by education, qualifications and work experience, but by their ability to effectively use digital tools [2, 3].

This process is multifactorial and nonlinear, as it is determined by a number of interrelated socio-economic, technological, institutional, and demographic factors [4]. Initially, under the influence of breakthrough technologies, the technological system of society is structurally renewed, giving impetus to qualitative changes within the socio-economic and institutional spheres of social organization [5]. Under the pressure of new technologies, socio-cultural institutions and dominant models of economic coordination are modified, and the role of the state is radically changed. At the same time, the issue of regulating processes related to changes in traditional employment models, the establishment of new forms of management, and economic security systems becomes acute [6].

Under such conditions, socio-economic relations acquire new forms and meanings, primarily due to the changing role and place of people in production processes. New digital technologies release a significant part of the workforce from direct production and, in return, create a very small number of jobs in high-tech sectors of the economy. This is an objective process. At the same time, they give impetus to the emergence and development of new areas of economic activity supported by these technologies. Empirical studies of the last decade prove that, despite digitalization and automation, regional labor markets are still achieving fairly high rates of employment growth [7]. This is evidence not only of changes in forms of employment, but also of structural transformations of a transformational nature.

Such interrelated and interdependent processes require effective coordination based on consideration of the system of factors of technological change and their socio-economic consequences in the field of employment.

Literature review. The complexity and non-linearity of the impact of post-industrial transformations on all spheres of society is one of the main topics of contemporary scientific research. In an attempt to establish causal links between the introduction of digital technologies and changes in employment in all socio-economic and institutional contexts, researchers have come to understand the profound interdependence between these processes.

For example, Goos M., Manning A., and Salomons A. found polarization of jobs in 16 Western European countries between 1993 and 2010, which was caused by technological changes. The researchers recorded an increase in the share of employment of highly paid specialists and managers, as well as low-paid workers in the service economy. On the other hand, a decrease in jobs in the direct production sector was observed [8].

Further research has deepened these ideas. In particular, Liu J., Tang Q., and Ayangbah F., based on the data from companies listed on the stock exchange from 2011 to 2021, found that the impact of digitalization on employment is not a simple linear relationship, but is subject to the “double threshold effect”: when the level of digital innovation reaches a certain threshold, the effect of promoting employment becomes more significant [9].

This relationship is substantiated by studies that address the impact of digital skills of personnel, relevant technologies, and knowledge concentrated within the internal environment of enterprises on overall employment processes and social inequality across the entire national economy. Giovannoni D., Knoesen E., and Mentz J. established a direct relationship between the level of technology in companies and employment in the country. It turned out that when companies introduced more advanced technologies into their activities, this increased the level of unemployment, particularly for the sector of the population with low digital skills [10]. Italian researchers Cirillo V., Mina A., and Ricci A. proved that digitalization causes a profound reorganization of work processes within a company. The scientists found a strong correlation between the introduction of new digital technologies and certain forms of lean production. They also proved the impossibility of completely replacing human labor, given the need for a certain degree of creativity and flexibility in the production process [11].

Structural transformations in the sectoral structure of the economy and their impact on employment are being actively studied by Chinese researchers. This is because it was in this country that a successful policy of transition to an innovative path of development was implemented, which brought it to the forefront of global technology leaders. Liu L., Wu C., and Zhu Y. analyzed the impact of industrial policy, which was implemented in the form of stimulating strategic industries, on employment. To measure the impact of structural changes in such industries on employment, the authors constructed a regression equation, which showed that the rate of technological change in strategic industries is unstable and negatively correlated with employment [12].

Gao J., Li Z., Nguyen T., and Zhang, W. came to the same conclusion. The researchers used regression modeling to measure the implementation of digital technologies at the enterprise level and to determine the relationship between digital transformation and employment. They found that the adoption of digital technologies such as artificial intelligence, big data, cloud computing, and blockchain is accompanied by a significant reduction in overall employment in enterprises. The scale of this reduction is greater in industrial sectors where there is less competition. At the same time, the researchers emphasize that digital transformation has the potential to improve the structure of employment in enterprises by increasing the share of well-educated and highly skilled workers [13].

Porzio T., Rossi F., and Santangelo G. confirmed the existence of a link between human capital and structural transformation of the economy. Using information on the level of education in cohorts of employed persons and data on educational reforms in countries with different levels of economic development, the researchers showed that the increase in the level of education for newer cohorts contributed to a reduction in employment in traditional industries [14].

Matthess M. and Kunkel S., researching the problem of possible potential links between structural changes in the labor market and digitalization, used an integrated methodological approach based on understanding of the interdependence and mutual influence of these processes [15]. The researchers conclude that, first, digitalization processes contribute to increased productivity in certain sectors of the economy, but there is no evidence that the structural changes in employment caused by these processes will be accompanied by equal gains from technological progress for those employed. Secondly, according to the authors of this work, the need to upgrade the skills of employees as a result of the introduction of digital technologies increases the degree of risk not only for fair income, but also for intercompany relations. The researchers also note that the claim that digitalization helps developing countries get a better spot in global markets is up for debate. This is because there is a chance that their participation in global value chains could shrink due to the relatively bigger advantages for developed countries. Therefore, as Matthess M. and Kunkel S. rightly point out, there is an urgent need for further empirical research aimed at identifying the interaction between structural change and digitalization processes in relation to specific technologies, industries, and countries.

One such study is the work by Sen K., in which the researcher investigated the consequences of post-industrial transformations in countries with different levels of development. The scientist proved that in low-income economies, a completely different mechanism of transformational changes in employment operates compared to rich countries [16].

Our previous studies came to a similar conclusion, revealing a correlation between technical and technological development and profound transformations in the qualities of the workforce. Based on statistical data from 26 countries around the world, the dominant role of innovative intellectual and social capital in economic development was proven. The calculated indices of these types of capital showed a strong bilateral direct relationship between the indicators studied. This serves as an argument to explain the unevenness of global economic development. Poor countries do not have sufficient resources to build up social and intellectual capital and, therefore, cannot fully use these resources to improve their final economic development indicators and achieve their economic interests in the global space [17, 18].

Ukrainian researchers Revenko D., Romanenko Yu., Polozova T. and Lebedchenko V., studying the impact of digitalization processes on the economic growth of the European Union, came to the conclusion that the introduction of modern technologies in high-income countries allows the population to fully realize their intellectual and creative potential through employment in high-tech sectors of the economy and areas of knowledge-intensive services [19]. To prove the hypothesis of the positive impact of digitalization on economic development, the researchers used a neoclassical production function model in which digitalization is an external or internal quasi-variable that has a separate or global impact on capital, labor, and overall productivity. The use of this model allowed researchers to find that the level of digital transformation of the labor market in countries with above-average income is significantly lower than in other countries. At the same time, it was found that the low prevalence of information and communication technologies in low-income countries makes it impossible for their populations to join the global digital labor market.

Other Ukrainian researchers [20] use regression modeling to figure out the possible link between the number of job openings on the labor market, on the one hand, and the number of companies providing Internet connection services, the number of companies engaged in e-commerce, and the number of economic entities operating in the field of "information and telecommunications" on the other. According to the results of this modeling, the most influential factor on the dynamics of vacancies in the labor market was the number of companies providing Internet connection services. The authors of this work also argue that the digitalization of the economy is a complex process that creates both additional opportunities and threats, especially in terms of employment.

An analysis of scientific publications has revealed arguments in favor of a certain connection between the processes of digitalization and structural changes in employment. However, these conclusions need further verification, given the more complex and multifactorial impact of digitalization on employment. It is necessary to identify the key factors that determine the trends, scale, and consequences of the digital transformation of employment, including its structure and contemporary forms.

Solving these problems requires the use of appropriate research methodology, as traditional methodological approaches have very limited capabilities for reproducing the complex logic of digital transformations and their consequences. This necessitates the use of tools capable of recording, structuring, and analyzing the multi-component interrelationships between influencing factors.

One such tool is cognitive modeling, which provides a structured cause-and-effect framework for the impact of digitalization on various aspects of employment. This approach allows us to identify the dominant factors of transformation and simulate possible scenarios for their course, taking into account the dynamics of change, the institutional context, and social consequences. Cognitive modeling is not just a means of visualizing complex systems; it is an analytical tool for strategic planning and supporting management decisions in the field of employment in the digital economy [21].

Despite the growing attention of the scientific community to the problems of digital transformation of employment, the application of the cognitive approach in this area remains fragmentary. The relevance of developing a cognitive model lies not only in its explanatory potential, but also in its practical ability to support the formation of adaptive, flexible, and strategically oriented employment policies capable of responding to the challenges of post-industrial transformations.

Purpose. To clarify the essence and consequences of the digital transformation of employment in the context of post-industrial transformations, to identify the key factors influencing the structure, forms, and dynamics of employment in the digital economy, and to subsequently develop a methodological approach to analyzing these changes based on cognitive modeling.

Methods. In the process of researching the transformation of employment in the digital economy, cognitive modeling was used as a tool for structural analysis of complex systems with multiple interdependent factors. The chosen approach ensures the formalization of qualitative information, visualization of cause-and-effect relationships, and modeling of the dynamics of the impact of individual factors on the structure of employment. This allows us to reproduce the logic of transformations that arise as a result of technological shifts, changes in qualification requirements, and the emergence of new organizational forms of labor. The research methodology is implemented through the construction of a cognitive model of digital transformation of employment, which reflects the systemic interaction of economic, technological, socio-demographic, institutional, and behavioral factors that determine changes in the field of employment. The structure of the model is based on an expert-analytical approach that takes into account both formalized and latent influences, especially in conditions of fragmentation or lack of reliable statistical data.

Results. Modern development has entered a new era in which digitalization is one of the key factors of economic and social transformation, as significant progress in digital technologies has brought about striking changes – from the way we communicate and access information to how we do business and interact with our environment. Digitalization has opened up new avenues for innovation, efficiency, and inclusion, bringing tangible benefits and new opportunities for individuals, organizations, and countries.

In theoretical economic discourse, digitalization is viewed, on the one hand, as a phenomenon that reflects a systemic change in the way economic value is produced, exchanged, distributed, and consumed through the widespread adoption of digital technologies. On the other hand, digitalization is seen as a process that involves the gradual introduction of digital solutions into all areas of society. These two aspects allow us to understand the essence of digitalization in all its causal relationships and, at the same time, to see the dynamic process of its unfolding and transformational impact. The latter is realized through a system of economic, political, social, and other factors.

These factors form the basis for the implementation of the proposed cognitive approach to the analysis of employment transformation. The development of a cognitive model involves the sequential identification and structuring of the main components of the system, the analysis of the cause-and-effect relationships between them, and the formalization of these relationships in a form convenient for further research. Cognitive modeling takes place in several interrelated stages: research on factors, model development, calculation of the degree of balance, and development of strategies for managing employment transformation.

Thus, at the first stage, an information base is formed, which is the basis for the further construction of a cognitive model. This makes it possible to take into account both general trends in digitalization and the specifics of the national labor market, which is critically important for further modeling. At the second stage, the cause-and-effect relationships between the factors influencing the structure of employment are visualized. The cognitive map created at this stage becomes a visual tool for analysis, as it reflects not only the key elements of the system, but also the nature of their interaction. At the third stage, a quantitative assessment of the impact of individual factors is carried out, which allows one not only to predict the consequences of changes, but also to identify critical points in the system that require special attention from management. This makes it possible to evaluate various scenarios for the development of the labor market and identify potential risks and opportunities associated with digital transformation. At the final stage, based on the results obtained, strategies and recommendations for managing the transformation of employment are developed. This includes the formation of mechanisms for staff adaptation, the development of retraining programs, the improvement of digital literacy, and the provision of social protection for employees. The implementation of cognitive modeling of employment transformations in the digital economy at the first and second stages made it possible to identify the key factors influencing the impact of digitalization on employment and to explore the relationship between them.

Economic factors in the context of digitalization are key determinants of employment transformation, causing changes in both the quantitative and qualitative parameters of the labor market. The shift in focus from physical capital to intellectual and digital resources is changing the structure of labor demand, causing a gap between employers' qualification expectations and the actual competencies of employees, and creating new challenges for the labor market in conditions of uneven access to technology and education.

One of the main economic triggers for these changes is investment in digital technologies. These investments are mainly directed toward production automation, the use of artificial intelligence, and the introduction of robotic systems and platforms for customer service. This contributes to increased labor productivity but leads to the displacement of workers involved in routine, monotonous operations. According to OECD experts, up to 14 % of all jobs are at risk of automation, and another 32 % may undergo significant changes in their functions [22]. At the same time, investment in innovation generates new forms of employment in the fields of digital development, IT infrastructure maintenance, data processing, and digital management. This process is accompanied by the formation of new professional niches and growing demand for specialists capable of working in a rapidly changing technological environment. A report on the future of jobs in 2025, prepared by experts from the World Economic Forum, notes that as a result of technological, economic, and demographic changes, 92 million jobs will be lost by 2030, while 170 million new jobs will be created, representing a net increase of 78 million [23]. The knowledge economy is replacing the industrial model of employment, with a focus on developing the creative, analytical, and interdisciplinary competencies of employees.

Another important economic factor is changes in the structure of labor demand caused by the transformation of the sectoral structure of GDP. Knowledge-intensive, service-oriented, and digital content sectors are showing growth in employment, while traditional manufacturing sectors are reducing their workforce. As a result, there is a stratification into highly skilled and low-skilled professions, with a simultaneous reduction in the middle class. Coursera's fourth annual report, which examines the critical skills that individuals and institutions will prioritize in 2025, notes that artificial intelligence skills are in highest demand worldwide. In 2025 alone, the number of registrations for courses that develop such skills increased by 866 % compared to last year [24]. Coursera's data in the report highlights a key trend in new technologies: the growing global adoption of generative artificial intelligence is leading to a sharp increase in demand for GenAI training. In countries with low digital infrastructure or insufficient access to retraining, the threat of long-term structural unemployment is growing.

The issue of unstable employment is becoming particularly relevant. With the spread of digital platforms, freelance models, and the gig economy, not only are work formats changing, but so is the economic logic of the labor market. Employers are increasingly less likely to enter into long-term contracts, preferring project-based or temporary employment. This leads to irregular income, a lack of social benefits, and reduced institutional protection for workers. Accordingly, new economic challenges are emerging for the social security system and labor law. In addition, the digitalization of employment is closely linked to macroeconomic fluctuations. During an economic upturn, companies have more resources to innovate and create new jobs. In contrast, during a crisis, investment activity declines and technological upgrades are suspended or postponed, which can partially stabilize employment levels in vulnerable (traditional) sectors. Thus, macroeconomic dynamics act as a restraining factor or catalyst for technological transformation of the labor market.

Government economic policy, which determines the scale and direction of digital transformation, is also a significant factor. Programs to support digital education, stimulate startups, invest in regional digital hubs, and develop e-governance create new employment opportunities. Conversely, the lack of an adaptive economic strategy in the digital sphere can lead to a loss of competitive advantages and an outflow of personnel. Thus, economic and political factors not only modify the structure of the labor market in the context of digital transformation, but also act as a catalyst for institutional changes related to employment, social protection, and professional mobility policies. Ensuring a sustainable transition to a digital economy requires comprehensive consideration of these factors in the process of forming a socio-economic strategy.

Human capital, as a stock of knowledge, skills, and motivations created through investment in education, health care, accumulation of professional experience, information search, labor mobility, etc. (Bekker, 1962), is also closely linked to employment and directly influences its structure. First, it is the realization of human capital that actually determines both the place of an individual in the system of social production, the content and form of their employment, and the structure of the labor market as a whole. Second, the development of individual and national human capital under the influence of scientific, technical, and technological changes is objectively accompanied by the acquisition of new knowledge, skills, and competencies, which are embodied in new professions and new professional experience, which also leads to structural changes in the labor market. And as practice shows, the development of human capital in the context of modern post-industrial transformation is primarily determined by the acquisition of digital skills and abilities by its carriers.

Social factors also have a close relationship with human capital and influence employment. Digitalization has changed social relations: thanks to the Internet, cloud services, and networks, people increasingly feel interconnected and globally united, increasing their level of individual social capital. It allows for a significant reduction in transaction costs and expands the scope of entrepreneurial activity and self-employment. At the same time, social capital, thanks to digitalization, promotes inclusiveness: it creates additional opportunities for people who face social barriers when looking for work or accessing production resources. This applies to the integration of women, people with disabilities, and residents of remote or mono-industrial areas. Targeted outsourcing can increasingly provide work via the Internet for poor and socially vulnerable segments of the population [25].

However, such opportunities are often limited by digital inequality, which manifests itself in two main ways. On the one hand, there is unequal access to digital technologies (due to insufficient income and limited development of information infrastructure), and on the other hand, there is unequal access to digital knowledge and the opportunity to acquire skills and competencies in their application. As practice shows, digital inequality manifests itself not only through limited access to the Internet and digital devices, but also through varying levels of digital literacy, which hinders full participation in new forms of economic activity. Rural residents, the elderly, low-income groups, and workers with low levels of education are particularly vulnerable. They fall into the so-called "digital poverty trap", where limited access to digital resources reproduces social marginalization and hinders the transition to new areas of employment.

Social and digital inequality directly affects employment levels in key sectors. For example, in the health, education, and social security sectors, the level of digital decision-making among employees is linked to the successful implementation of electronic technologies (eHealth, distance learning). In sectors with low digital culture or active resistance, the transition to new employment models is slower, which ultimately reduces the overall productivity and competitiveness of the economy.

Behavioral factors such as the ability to adapt to digital transformations, natural abilities and psychological characteristics of the individual, and the type of dominant culture also play an important role in this. Society's attitude toward digital change varies from active acceptance to open or latent resistance, which significantly affects individual employment trajectories and the effectiveness of the digital transformation of the economy. Adapting to the digital environment involves gradually learning new tools and changing professional behavior and expectations. Employees who have access to reskilling and upskilling programs and employer support demonstrate greater willingness and ability to adapt to new requirements. At the mega and macro levels, these groups of attitudes toward digital technologies form a kind of "behavioral map" of digital transformation. According to this map, regions are divided into those with a high level of acceptance and adaptation of digital technologies, which become centers of employment in the fields of ICT, finance, logistics, and creative industries, and regions with widespread resistance, which are experiencing the degradation of local labor markets, the loss of part of the population from productive employment, and increased social isolation.

The impact of this group of factors creates a situation where the dividends of digitalization are reaped by a more affluent, educated, and experienced workforce in terms of digital skills. It is this workforce that employers increasingly prefer, thereby creating digital unemployment and pushing those who, for various reasons, are unable to quickly develop their digital skills to the lower levels of the income pyramid. The compilation of factors influencing employment in the context of digitalization in Table 1 and the selection of indicators for their quantitative assessment complete the first two stages of cognitive modeling.

The third stage involves calculating the degree of balance of the cognitive model $b(G)$, which will allow us to assess how consistent the relationships between its elements are and how they interact within the system. It is the ratio of the number of positive contours of the formed orgraph to their total number, provided that $b(G) \in [0; 1]$

$$b(G) = \frac{\sum_{k=3}^{c} \frac{1}{k} p_k}{\sum_{k=3}^{c} \frac{1}{k} t_k}, \quad (1)$$

where p_k is the number of positive cycles of length k; t_k is the total number of cycles of length k; c is the length of the longest cycle in the orgraph G [26].

If $b(G) = 0$, the orgraph is considered balanced, and if $b(G) = 1$, it is considered unbalanced. The constructed model revealed 128 contours, of which 71 are amplifying and 57 are stabilizing. This indicates that the system is dominated by processes that amplify influences, but a significant number of stabilizing contours ensure

Table 1

Factors and indicators of employment transformation in the digital economy

Group of factors	Indicators
Result indicator	Share of employment in the digital economy in the total employment structure (v_1)
Digitalization	Level of digital infrastructure (v_2) Investment in digital technologies (v_3) Implementation of automation of routine tasks, robotization (v_4) Distribution of digital platforms for employment (v_4) Global technological trends (v_6)
Socio-behavioral factors	Social and digital inequality (v_7) Population's attitude towards digital technologies (acceptance, resistance, adaptation) (v_8)
Economic factors	Changes in employment levels in key sectors (v_9) Unemployment levels among different categories of workers (v_{10})
Human capital	Professional and qualification skills (v_{11}) Level of digital literacy of the population (v_{12}) Availability of reskilling/upskilling programs (v_{13})
Regulatory factors	Availability of a state digital strategy (v_{14}) Level of business support for digital transformation (v_{15})

the system's ability to self-regulate and prevent excessive fluctuations. This structure gives hope for the effective functioning of the model, as it combines both development and stabilization mechanisms, which is important for maintaining the stability and adaptability of the system. Then the measure of balance of the model is

$$b(G) = \frac{\frac{1}{1}\cdot 3+\frac{1}{2}\cdot 3+\frac{1}{3}\cdot 6+\frac{1}{4}\cdot 23+\frac{1}{5}\cdot 18+\frac{1}{6}\cdot 11+\frac{1}{7}\cdot 7}{\frac{1}{1}\cdot 5+\frac{1}{2}\cdot 3+\frac{1}{3}\cdot 6+\frac{1}{4}\cdot 26+\frac{1}{5}\cdot 38+\frac{1}{6}\cdot 18+\frac{1}{7}\cdot 21+\frac{1}{8}\cdot 10+\frac{1}{9}\cdot 1} = 0.478.$$

A balance measure of 0.478 indicates a balanced system structure, in which reinforcing and stabilizing influences are present in approximately equal amounts, ensuring a balance between the potential for development and self-control. Such a system is not overly rigid, is not prone to excessive amplification of changes, and can respond effectively to external factors while maintaining stability without the risk of unpredictable fluctuations. However, since the value is close to the middle of the range, it is important to conduct additional analysis of development scenarios to identify factors that could upset the balance and predict their impact on the overall effectiveness of the system. In general, this value of the balance measure indicates that the system is fairly balanced but requires careful monitoring to maintain an optimal balance between development and stability.

Next, the fourth stage of cognitive modeling begins – the implementation of the impulse process of employment structure transformation. Based on the constructed symbolic orgraph, an adjacency matrix ($A_G = A = |a_{ij}|_{n\times n}$) is formed under the following condition

$$\operatorname{sgn}(u_j,u_i) = \begin{cases} 1, & \text{if edge } (u_j,u_i) \text{ is positive} \\ -1, & \text{if edge } (u_j,u_i) \text{ is negative.} \\ 0, & \text{if edge } (u_j,u_i) \text{ is missing} \end{cases} \quad (2)$$

The definition of an autonomous impulse process is carried out by the classical method proposed in (Roberts F., 1976)

$$v_i(t+1) = v_i(t) + \sum_{i=1}^{n} \operatorname{sgn}(u_j,u_i)\, p_j(t), \quad (3)$$

where $v_i(t)$ is the momentum value at the i^{th} vertex at the previous moment (simulation cycle); $v_i(n+1)$ is the value of the impulse at the i^{th} vertex at a specific moment for the researcher $(n+1)$; $p_i(n)$ is the vector of disturbances and control influences entering the vertex at moment (n).

To implement the impulse process, disturbing impulses were introduced in stages into individual vertices of a constructed oriented graph (orgraph), which reflects the cognitive model of interrelationships between key factors influencing the transformation of the employment structure in the digital economy. At each stage of modeling, it was recorded how a single disturbance in a separate factor (node) is transmitted through the network of interdependencies and how it affects the target vertex – v_1 "Share of those employed in the digital economy". This approach made it possible to identify the strength, direction, and nature of the impact of individual factors on transformation processes in the field of employment.

As a result of the calculations, a set of scenarios for the possible development of the situation (cognitive model) was formed, demonstrating different trajectories of changes in the structure of employment depending on which factor initiates the disturbance of the system (Fig. 1).

Scenario 1. A disruptive positive impulse is given to vertex 2 (digital infrastructure level) – $imp_2(t) = (0, 1, 0, \ldots, 0, 0)$. The result of the impulse modeling is shown in Fig. 2.

Fig. 2 shows that the dynamics of the share of people employed in the digital economy, assuming growth in the level of digital infrastructure, has a pronounced upward trend: there is a gradual and steady increase in the number of workers involved in the digital sector. The development of digital infrastructure directly contributes to the creation of new jobs in the field of digital technologies, stimulating structural changes in the labor market and increasing demand for specialists with digital competencies.

Particularly noticeable are sharp growth spurts at certain stages, which indicate periods of active digital transformation, the introduction of innovative technologies, and the scaling of digital projects. This, in turn, not only contributes to higher employment in the digital economy, but also provides a foundation for the further development of related industries, the formation of new professions, and increased competitiveness of the economy as a whole.

Scenario 2. The initial impulse is given to vertex 3 (investments in digital technologies) – $imp_3(t) = (0, 0, 1, 0, \ldots, 0, 0)$, which leads to the activation of digital transformation processes in the relevant sectors of the economy, stimulates the implementation of innovative solutions, and increases the efficiency of production and management processes (Fig. 3).

As a result of impulse modeling, there is an increase in the share of people employed in the digital economy,

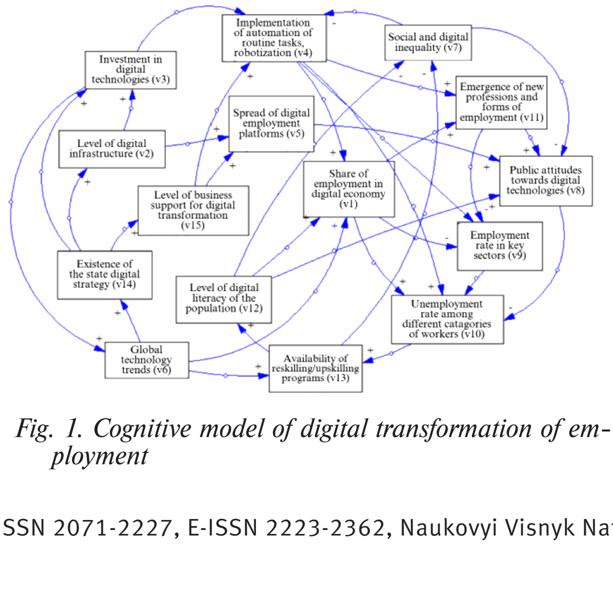

Fig. 1. Cognitive model of digital transformation of employment

provided that investment in digital technologies increases. This dynamic is driven by the acceleration of digital business transformation processes, the emergence of new forms of employment, and growing demand for workers with relevant digital skills. Attracting capital to the digital sphere stimulates the development of innovative products and services, the transformation of traditional business models, and the creation of new jobs in industries related to information technology, artificial intelligence, data analysis, and the Internet of Things.

Scenario 3. The impulse is given to vertex 4 (implementation of automation of routine tasks, robotization) – $imp_4(t) = (0, 0, 0, 1, \ldots, 0)$ (Fig. 4).

In the early periods (1–3), there is a decline in momentum, indicating short-term adaptive inertia of the system. Starting from the fourth period, momentum shows a gradual increase, with slight volatility in the middle stages (periods 6–9) and steady acceleration in the final periods. This indicates that the system is entering a phase of active transformation, when the positive effect of technological disruption begins to manifest itself fully.

Thus, the growth in the number of implementations of automation of routine tasks and robotization of production and service processes contributes to a gradual increase in the share of those employed in the digital economy. This is due to a shift in focus from traditional forms of employment to activities related to the management, support, and development of digital systems.

Scenario 4. The initial impulse is given at vertex 6 (global technological trends) – $imp_6(t) = (0, 0, \ldots, 1, \ldots, 0)$ (Fig. 5).

Scenario modeling demonstrates a steady upward trend in the share of people employed in the digital econ-

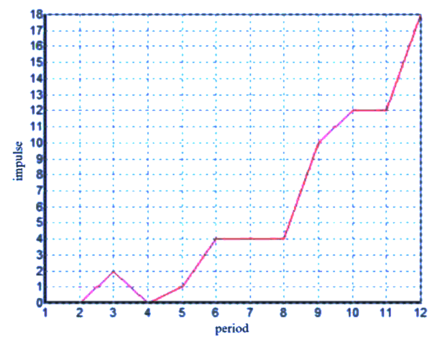

Fig. 2. Scenario of changes in the share of people employed in the digital economy in the overall employment structure, assuming growth in the level of digital infrastructure

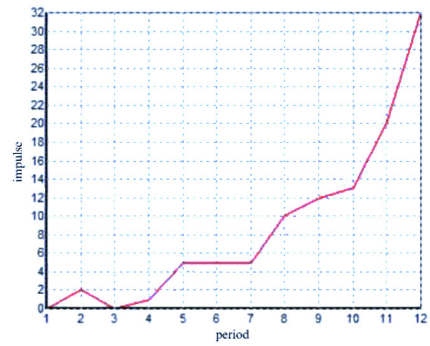

Fig. 3. Scenario of changes in the share of people employed in the digital economy, assuming growth in investment in digital technologies

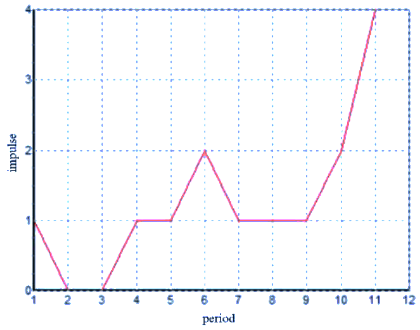

Fig. 4. Scenario of changes in the share of people employed in the digital economy in the context of automation and robotization

omy amid intensifying global technological trends. Only in the sixth period is there a slight temporary decline, due to the adaptive inertia of the system, delays in retraining workers, or short-term structural imbalances between the supply and demand for digital skills. In subsequent periods, the dynamics show stable growth, indicating the effect of scaling digital solutions, growing sustainable demand for digital specialists, and the gradual overcoming of transformation barriers. This dynamic is driven by several key factors. First, the active introduction of digital technologies in various sectors of the economy contributes to the expansion of demand for specialists involved in the development, implementation, and support of digital solutions. This applies to industries working with big data, cloud services, artificial intelligence, automated management systems, and the Internet of Things. Second, the structural transformation of business models and the transition of companies to digital formats of activity stimulates the creation of new forms of employment, particularly in the gig economy, remote work, and digital entrepreneurship. Thirdly, global investment trends show a shift in priorities towards digital infrastructure, digital services, and technology startups, which accelerates the formation of a digitally oriented labor market. Finally, adapting the education system and improving the digital literacy of the population allows broader segments of the population to integrate into the digital economy, further reinforcing the positive trend.

Scenario 5. The impulse is given at vertex 9 (change in employment levels in key sectors) — $imp_9(t) = (0, 0, ..., 1, ..., 0)$ (Fig. 6).

Fig. 6 demonstrates the uneven dynamics of the share of those employed in the digital economy, which is shaped by changes in employment levels in key sectors. During the first six periods, there is a relative stabilization of the share of employed persons, which indicates the inertial nature of transformations and the limited response of the digital sector to initial fluctuations in the basic sectors of the economy. This is followed by a temporary decline in the share of digital employment, which may be related to the redistribution of labor resources, an adaptive decline, or a drop in employment in sectors with weak links to digital industries. From period 9 onwards, the share rises again, indicating the intensification of the impact of sectoral shifts, in particular the decline in employment in traditional industries (e.g., manufacturing, agriculture) and the flow of personnel to the digital sphere. Periods 12—13 show a sharp decline, which may be caused by crisis processes, the exhaustion of the spillover effect, or limited absorption by the digital sector. In subsequent periods, there is a rapid increase in the share of people employed in the digital economy, indicating a turning point in the transformation, possibly due to the large-scale introduction of technologies, labor market reforms, or accelerated automation in key sectors.

Scenario 6. The initial impulse is given at vertex 13 (availability of reskilling/upskilling programs) — $imp_{13}(t) = (0, 0, ..., 1, 0, 0)$ (Fig. 7).

In the initial periods, the share of people employed in the digital economy shows a slight but steady increase, indicating a moderate initial impact of reskilling/upskilling programs, which in the early stages are implemented on a selective or pilot basis, without covering broad segments of the population. In periods 5—6, there is a decline in momentum, which may be due to the labor market's insufficient adaptation to new skills or a temporary decline in the activity of training programs or their funding. Periods 7—9 show an acceleration in the growth of the share of people employed in the digital economy. This is explained by the more widespread implementation of retraining programs, support from the state and business, and growing demand for digital skills. This phase reflects the gradual expansion of workers' opportunities to adapt to new labor market conditions, but in periods 11—12, the dynamics stabilize, indicating that the programs have reached their short-term effectiveness limit or that there is a need for a qualitative update of educational and structural approaches. In recent periods, there has been a rapid increase in the share of people employed in the digital economy, which indicates the cumulative effect of previ-

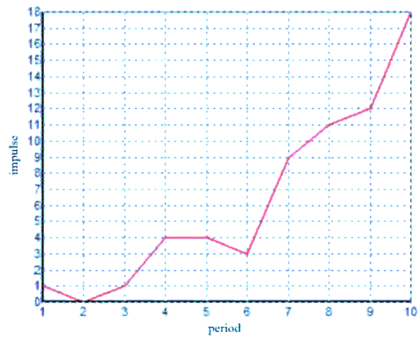

Fig. 5. Scenario of changes in the share of people employed in the digital economy under the influence of global technological trends

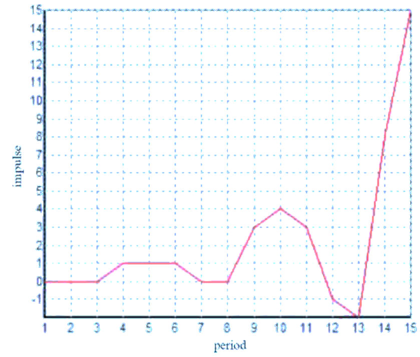

Fig. 6. Modeling changes in the share of digital employment under the influence of cross-sectoral shifts in the labor market

ous investments in human capital development. This may be due to the achievement of a critical mass of retrained personnel capable of filling new digital positions, as well as the transformation of traditional sectors of the economy towards digitalization, which opens up new employment opportunities in high-tech industries. Therefore, the results confirm that investment in retraining and upskilling of workers is a strategically important factor in the formation of a digital economy. Although the effect of such programs is not immediate, it manifests itself in the long term through the accumulation of human capital and structural shifts in employment.

Scenario 7. The impulse is given to vertex 14 (presence of a state digital strategy) – $imp_{14}(t) = (0, 0, \ldots, 0, 1, 0)$ which activates systemic processes of forming a digital transformation policy, promotes the integration of digital technologies into public administration (Fig. 8).

The existence of a state digital strategy has a positive impact on employment dynamics in the digital sector, as confirmed by a steady upward trend. Such a strategy acts as a catalyst for structural changes in the labor market, contributing to the creation of new jobs in IT, cybersecurity, data analysis, digital administration, and other areas of the digital economy. This not only expands employment opportunities but also contributes to the modernization of the employment structure as a whole. Institutional support in the form of a digital strategy ensures coordination between the state, business, and education, which contributes to increasing the digital literacy of the population. The predictability and consistency of state policy in the field of digitalization creates a favorable environment for business, allowing the private sector to plan digital transformations in advance and proactively attract IT specialists. International experience of countries with developed digital strategies (in particular, Estonia, Singapore, and South Korea) confirms that a systematic approach to digitalization is accompanied not only by growth in digital employment, but also by a gradual reduction in social and digital inequality, thanks to expanded access to digital services, education, and opportunities for self-realization in the digital environment. This is precisely the dynamic demonstrated by impulse modeling, which shows a correlation between the existence of a national digital strategy, growth in digital employment, and a reduction in the digital divide (Fig. 9), indicating its relevance and alignment with global trends.

Scenario 8. In order to model the combined impact of key factors on the model, we will set the initial impulse at two vertices: the level of digital literacy of the population and the availability of reskilling/upskilling programs – $imp_{12,13}(t) = (0, 0, \ldots, 1, 1, 0, 0)$ (Fig. 10).

Fig. 10 shows that in the initial stages there is a slight increase in the number of people employed in the digital sector, but after a certain period of intensification of reskilling and upskilling programs, as well as an increase in the level of digital literacy, there is a noticeable acceleration in employment rates. This indicates a positive correlation between investment in professional development of personnel and growth in the number of employees in the digital sphere. The results confirm that the systematic implementation of educational initiatives aimed at developing digital competencies has a cumulative effect and significantly influences employment indicators in the digital sector. Thus, the development of digital literacy and the continuous updating of skills are key factors in ensuring sustainable economic growth and competitiveness in the context of digital transformation.

Scenario 9. As part of modeling the combined impact of key factors on the model, we will set the initial impulse at two vertices: the level of digital literacy of the population and the level of business support for digital transformation – $imp_{12,15}(t) = (0, 0, \ldots, 1, 0, 0, 1)$ (Fig. 11).

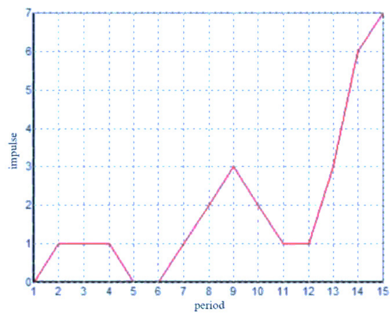

Fig. 7. Impact of reskilling and upskilling programs on employment dynamics in the digital economy

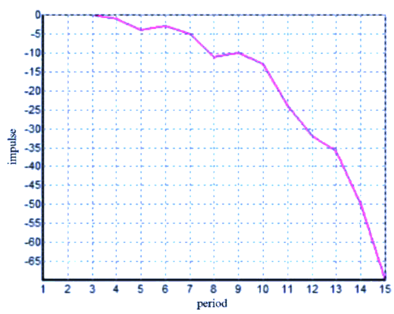

Fig. 9. Reduction of digital inequality in the context of implementing a digital strategy

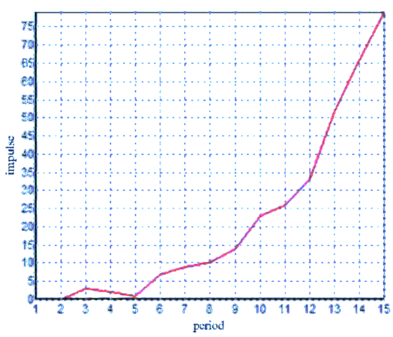

Fig. 8. The role of the state digital strategy in shaping employment trends in the digital sector

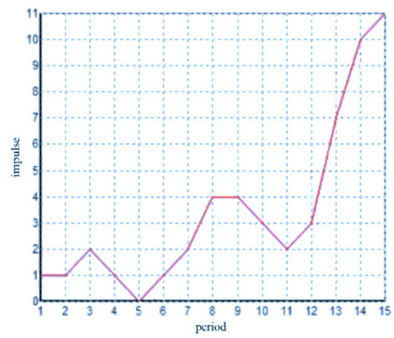

Fig. 10. Impact of digital literacy and reskilling/upskilling programs on employment in the digital sector

The analysis of the dynamics of employment in the digital sector, shown in Fig. 11, reveals a nonlinear nature of change, which is associated with the initial phase of adaptation to the new conditions of digital transformation. In the initial stages, there is a stabilization of indicators, followed by a temporary decline in employment, which may be due to structural changes, reorganization of business processes, or the need for staff retraining. This confirms the importance of taking time lags into account when assessing the effectiveness of investments in digital literacy and business support. In the longer term, after overcoming the initial difficulties of adaptation, there is steady and accelerated growth in employment in the digital sector. This indicates the cumulative effect of systematic support for the development of digital competencies and the active introduction of innovative approaches in the business environment. Thus, the integration of digital literacy and business support for digital transformation is a key factor in ensuring long-term employment growth in the digital economy.

Conclusions. Post-industrial transformations are taking place under the influence of breakthrough technologies that are revolutionizing all spheres of society. They are based on digitalization, which is systematically changing the very ways in which economic value is created and, at the same time, involves the phased introduction of digital solutions.

The transformative impact of digitalization affects employment – its very nature is changing. This is happening due to a system of economic, political, social, and other factors. The most significant of these are economic, regulatory, human capital, and socio-behavioral factors. Taking into account their impact on employment in the process of digitalization requires the creation of a methodological approach that would allow us to consider the impact of post-industrial transformations on employment in the entirety of interrelationships and interactions.

Cognitive modeling is a powerful tool for structuring complex economic and social problems, as it allows formalizing the relationships between key factors, predicting the consequences of management decisions, and developing optimal strategies for adapting to dynamic changes. This method makes it possible not only to quickly assess the current state of the system, but also to quickly identify the main cause-and-effect relationships, allowing the most effective paths for development to be chosen.

The results of applying cognitive modeling show that, in the context of digital transformation, there is a gradual and sustained change in the structure of employment in favor of the digital sector. This process is most influenced by the growth of digital infrastructure, increased investment in digital technologies, the introduction of automation and robotization in production processes, the strengthening of global technological trends (manifested in the scaling effect of digital solutions), growing steady demand for digital specialists, and the gradual overcoming of transformation barriers. Changes in the share of digital employment were also identified under the influence of cross-sectoral shifts in the labor market, the implementation of the state digital strategy in shaping employment trends in the digital sector, the reduction of digital inequality, the growth of digital literacy, and the implementation of reskilling/upskilling programs.

Understanding these influences and their consequences enables comprehensive strategic planning in the areas of employment, education, and innovative development. This will contribute to the formation of adaptive employment policies capable of ensuring flexibility, social stability, and competitiveness of the national labor market in the long term.

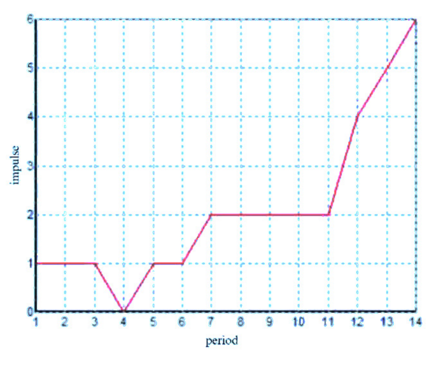

Fig. 11. Impact of digital literacy and business support for digital transformation on employment in the digital sector

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Постіндустріальні трансформації суспільства та їх вплив на структуру зайнятості

Е. В. Прушківська[1], *Ю. І. Пилипенко*[*2], *А. М. Ткачук*[2], *Г. М. Пилипенко*[2], *В. О. Лось*[3]

1 – Національний університет біоресурсів та природокористування, м. Київ, Україна
2 – Національний технічний університет «Дніпровська політехніка», м. Дніпро, Україна
3 – Київський столичний інститут імені Бориса Грінченка, м. Київ, Україна
[*] Автор-кореспондент e-mail: pylypenkoyi@gmail.com

Мета. З'ясування сутності й наслідків цифрової трансформації зайнятості в умовах постіндустріальних трансформацій, виявлення ключових чинників, що впливають на структуру, форми й динаміку зайнятості у цифровій економіці з подальшим формуванням методологічного підходу до аналізу цих змін на основі когнітивного моделювання.

Методика. У дослідженні використано когнітивне моделювання як міждисциплінарний інструмент для аналізу трансформації зайнятості в умовах цифрової економіки. Методологічну основу становить системний підхід до ідентифікації та формалізації складних причинно-наслідкових взаємозв'язків між економічними, технологічними, соціально-демографічними, інституційними чинниками, що зумовлюють зміну структури ринку праці. У процесі моделювання використана експертно-аналітична база знань, що забезпечує репрезентативне відображення сучасних трансформаційних тенденцій, зокрема динаміки формування нових форм зайнятості (гіг-економіка, дистанційна праця) і поступової редукції традиційних форм трудової участі. Такий підхід дозволяє ефективно досліджувати недостатньо структуровані або слабо формалізовані процеси, характерні для умов стрімкої цифровізації.

Результати. Розроблена когнітивна модель трансформації зайнятості, що візуалізує взаємозв'язки між основними факторами цифровізації та структурними зрушеннями на ринку праці. Визначені ключові впливи технологічного прогресу на зміну попиту на працю, професійну мобільність, динаміку виникнення нових професій і трансформацію трудових відносин. Модель дозволяє формувати сценарії розвитку зайнятості в умовах цифрової економіки й адаптувати політику ринку праці до нових викликів.

Наукова новизна. Обґрунтована доцільність використання когнітивного моделювання як інструменту дослідження трансформації зайнятості, що забезпечує глибше розуміння структурних змін на ринку праці в умовах цифровізації. Розроблена концептуальна модель, що поєднує технологічні, соціальні й економічні аспекти постіндустріальних змін і дозволяє прогнозувати їхній вплив на зайнятість, виявляти приховані взаємозв'язки та створювати основу для прийняття стратегічних управлінських рішень.

Практична значимість. Результати дослідження можуть бути використані для вдосконалення стратегій управління зайнятістю в умовах цифрової трансформації економіки. Запропонована когнітивна модель цифрової трансформації зайнятості дозволяє ідентифікувати ключові чинники, що визначають динаміку змін у структурі ринку праці. Поряд із цим, за її допомогою можна здійснювати оцінку ризиків і потенціалу автоматизації в різних секторах економіки, моделювати сценарії розвитку зайнятості залежно від рівня цифровізації. Практичне застосування результатів когнітивного моделювання дозволить формувати більш ефективні напрями політики зайнятості, здатної забезпечити гнучкість, соціальну стійкість і конкурентоспроможність національного ринку праці у довгостроковій перспективі.

Ключові слова: *цифровізація, постіндустріальна трансформація, зайнятість, структура зайнятості, ринок праці, когнітивне моделювання*

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