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The transformation of labor in the digital age: Matching skills to job requirements

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Abstract

Digital transformation is a process of change characterized by the deep integration of new technologies such as big data, artificial intelligence, and blockchain. The extensive collection, storage, and analysis of internal and external company data provide an accurate foundation for decision-making; AI systems offer intelligent functions for analysis, forecasting, and decision-making to automate and optimize processes. The article presents the results of a study on the impact of digital transformation on professional development and working conditions. The analysis is based on survey data covering organizational, functional, market, and personal factors. The use of stepwise regression modeling made it possible to identify key predictors, such as regional differences in digital infrastructure and the interaction of skills with individual growth support. The identified negative relationship between digital skills and the level of workplace digitalization indicates potential adaptation barriers. Organizational variables mainly influence through mediating mechanisms. Interacting factors demonstrate a synergistic effect, confirming the importance of a comprehensive approach to managing digital change. Correlation-regression analysis also revealed moderate multicollinearity between variables, requiring additional attention when interpreting the models. The results have practical significance for developing digitalization strategies focused on supporting and developing personnel in various regional contexts.

Keywords: Digital technologies, Digital transformation.

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1. Introduction

Thanks to the continuous modernization and rapid popularization of digital technologies and mobile Internet, the wave of digitalization is gaining momentum worldwide, and the digital economy has seized this trend and is developing rapidly. In the digital economy, data is becoming an increasingly important factor of production. The widespread adoption of digital platforms has subtly transformed production methods, organizational structures, and work practices, gradually leading to the creation of new resources for employment and opportunity distribution. This may result in the restructuring of production relations in related industries and even the economy as a whole, potentially having a profound impact on the volume, structure, forms, and quality of employment. Therefore, it is necessary to take advantage of the current situation, fully leverage strengths, address weaknesses, avoid risks, develop a new model suitable for effectively coordinating the development of the digital economy and the labor market, and design a policy system that promotes high-quality and full employment, as well as job search in the new environment.

The digital economy has a profound impact on the traditional labor market, as automation and artificial intelligence have replaced a large number of conventional jobs. In light of these changes, employees must constantly upgrade their skills, while governments and companies should provide appropriate support and training programs to address shifting employment models.

With the development of digital technologies, a new generation of automated systems and intelligent solutions has emerged in the labor market, increasingly displacing routine and standardized tasks. Machine learning and AI-based programs are now performing tasks that were once considered exclusively human, such as data analysis, diagnostic project management, and even creative processes. This has led to job losses in certain regions, resulting in rising unemployment and labor market inequality, particularly among workers with outdated skills.

However, digital transformation not only eliminates traditional professions but also creates new opportunities. Occupations directly related to the development and implementation of digital technologies are emerging, including programming, cybersecurity, data analysis, AI systems management, and more. These changes require employees to acquire new skills and knowledge in digital technologies, manage large volumes of information, and adapt to the rapid pace of innovation. This creates a shortage of qualified professionals capable of meeting the growing demand for digital skills.

The aim of this study is to analyze the alignment between existing employee skills and the demands of digital transformation at the regional and workplace levels. The mismatch between skills and the needs of the digital economy is reflected in a growing "skills gap" between worker qualifications and current labor market requirements. This gap hinders the effective implementation of digital technologies and reduces workforce competitiveness.

The novelty of the study lies in identifying and systematizing new forms of "competency mismatch" under conditions of digital transformation. The article presents an original model for assessing the alignment of digital competencies with professional requirements.

The importance of digital skills is evident in the National Strategy; however, a significant issue is the widespread shortage of employees possessing these skills in our country. The challenge of digital transformation does not lie in the number of available jobs but in the scarcity of talent with digital competencies. On one hand, employees lacking digital skills often feel helpless, even if they are willing to work with people and computers and perform various support functions [1]. On the other hand, modern skills are often poorly suited to the demands of a rapidly evolving workplace. Given the current situation, the gap in hiring qualified specialists is becoming more evident. There is high demand for advanced technical positions, yet a shortage of suitable professionals. This phenomenon highlights challenges in the provision of vocational education.

As central institutions for training qualified professionals, polytechnic institutes and universities play a significant role in educating specialists with digital skills and preparing them for digital work. The inevitable trend of digital transformation clearly requires accelerated development and training of vocational students in digital competencies [2]. However, determining which digital skills vocational students should acquire and how they can develop them remains a question that must be addressed at this stage.

Considering global efforts to develop digital skills systems, this study examines digital changes in work practices and integrates digital competency frameworks proposed by other countries and international organizations to summarize the existing digital skills relevant to vocational school and university students.

2. Literature Review

Digitalization is viewed as a potentially significant driver of innovation and economic growth, leading to increased productivity and the development of new products and services [3]. However, it may result in the creation or elimination of jobs, inevitably causing changes in the structure and polarization of the labor market. Digitalization contributes to the spread of new forms of employment, such as online or remote work, which have a substantial impact on labor organization and the interaction between employers and employees. In current labor market research, the COVID-19 pandemic has not gone unnoticed; it can be observed that labor market changes have intensified since the pandemic. Currently, many authors are studying the impact of digitalization on the labor market, particularly in companies that primarily belong to small and medium-sized enterprises.

The development of the digital economy and the innovative use of digital technologies have led to both qualitative and quantitative changes in the labor market. On the one hand, this has resulted in significant changes in hiring practices, forms of employment, and skill requirements. On the other hand, it has had a dual impact on job numbers, leading to both job creation and job reduction effects, in addition to the distinct characteristics of the digital economy era.

Experience in the development of the digital economy in recent years has shown that digital transformation can serve as a tool to improve employee allocation and support the modernization of a company's value chain [4] and reduce operational activities and unproductive connections [5] thereby achieving a high level of alignment between human resources, production, and operational processes.

Digital transformation can help companies integrate internal and external resources, improve the efficiency of information flow within the value chain, expand the value chain, and recreate the logic of the division of labor and its functioning within the value chain, allowing for greater flexibility. It enhances the impact of information and resources on the value chain and strengthens the ability to effectively prepare and utilize resources [6-8].

Digital transformation in the labor market helps reduce demand for workers with lower levels of education while increasing demand for those with higher educational qualifications.

2.1. Теория Skills Gap and Skills Mismatch

The skills gap refers to the mismatch between the skills employers require and the skills possessed by job seekers and employees. It is projected that by 2028, the gross national product will be affected by reduced labor productivity due to a shortage of skilled workers [9].

According to policymakers, by 2030, 1.1 billion jobs worldwide will undergo fundamental changes, and employees will need to undergo reskilling to remain effective in their roles [10]. Although awareness of the need for upskilling and reskilling is growing, a gap has long existed between employers' expectations of employee qualifications and actual skill levels. For example, a report by the U.S. Chamber of Commerce in 2020 stated that 74% of 500 HR managers surveyed nationwide believed there was still a shortage of skilled personnel. Additionally, the report noted that 78% of respondents preferred to use alternative methods rather than rely on certificates or diplomas to assess candidates.

Another HR study also confirms a mismatch between the demand for and the supply of the aforementioned workplace skills [11]. For instance, the 2019 Job Outlook Survey, which included 172 employers from various regions and industries in the U.S., reported that only 57% of employers believed recent graduates possessed critical thinking or problem-solving skills. Given that 100% of employers rated this skill as very important, the gap indicates a significant skills mismatch [12].

A 2018 employer survey also showed that, regardless of profession, executives and HR managers frequently emphasized the importance of knowledge accumulation, critical thinking, and analytical skills [11]. However, critical thinking is not the only essential skill. The same report outlined the skills most valued by HR managers in new graduates, ranked as follows: verbal communication, critical/analytical thinking, ethical judgment and decision-making, teamwork, self-management/independence, motivation and initiative, written communication, and problem-solving/application of knowledge to practical tasks.

To understand the effectiveness of employment assessment, attention must be paid to comparative analysis during evaluation and subsequent labor market assessments. The gap between the skills workers possess and those employers need is a long-term issue that will impact economic development.

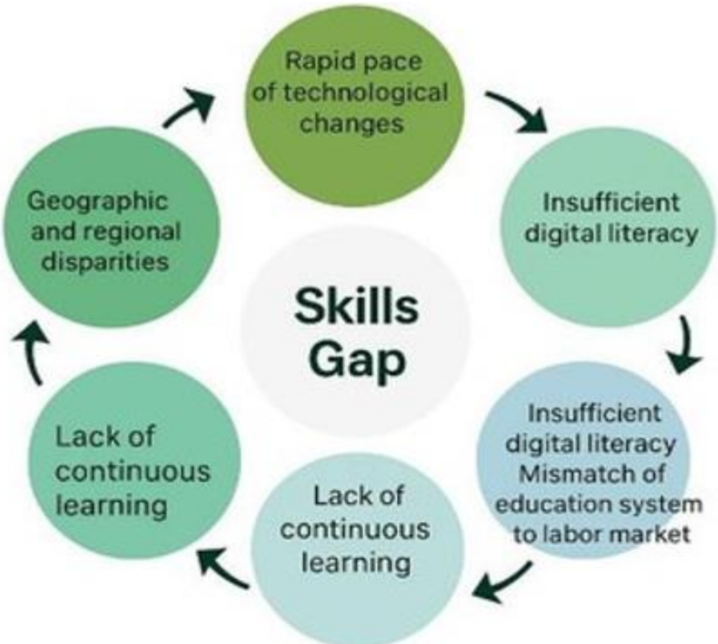

Figure 1.
Factors Contributing to the Shortage of Skilled Personnel in the Digital Economy.

The diagram illustrates six key factors contributing to the skills shortage, including rapid technological change, skill obsolescence, insufficient digital literacy, mismatch between education and market needs, lack of lifelong learning opportunities, and regional disparities (Figure 1).

Due to discrepancies between employers and employees regarding candidates' capabilities in the labor market, employers may rely solely on signaling mechanisms to assess applicants' potential. In such cases, the quality of the signal directly affects the efficiency of talent allocation and actual productivity. Developing countries face transitional constraints, especially when compared to highly competitive Western nations, such as imperfect market structures, inconsistent market laws, and underdeveloped legal and regulatory frameworks [13].

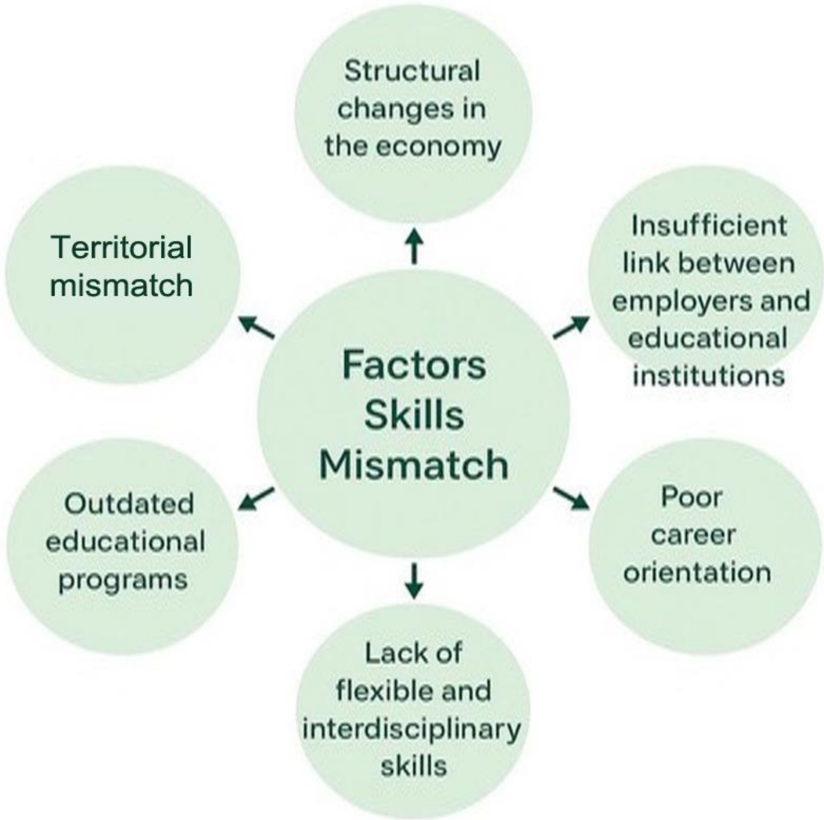

Figure 2.
Key Factors Contributing to Skills Mismatch.

The diagram illustrates the main causes of the mismatch between skills and labor market requirements. These include structural changes in the economy, outdated educational programs, weak links between employers and educational institutions, lack of soft skills, ineffective career guidance, and regional disparities (Figure 2).

The European Commission developed the DigComp model, which identifies five areas of digital competence: information literacy, communication, content creation, safety, and problem-solving. The authors emphasize the importance of digital skills as a key component of employee adaptation to new technologies [14, 15].

Digital skills are regarded as the foundation of employee competitiveness. Kazakhstani researchers analyze the requirements for digital competencies within the framework of Kazakhstan's digital transformation strategy [16-21].

According to a report by McKinsey & Company [22] the key factor for successful adaptation is on-the-job training and reskilling, and the importance of a culture of continuous learning and employee involvement in the change process is highlighted.

Research on academic qualifications and employment tends to focus on the negative effects of educational disparities on workers, with retraining gaps considered to have a negative impact on income. Moreover, educational inequality reduces job satisfaction, increases staff turnover, and ultimately lowers employees' subjective well-being. In contrast, knowledge, skills, and cognitive abilities that match job requirements can lead to increased labor productivity [23].

Given the new challenges that 21st-century economic development presents to workers, digital skills are not only basic practical abilities required for using information technologies but should also encompass communication, collaboration, critical thinking, creativity, and problem-solving skills. Individuals with low levels of digital literacy will be deprived of the benefits of the Internet, and this digital divide will further exacerbate their disadvantages. Moreover, groups with higher education and income levels tend to possess relatively more digital skills [24].

2.2. Model of the Impact of Digital Skills on Job Mismatch

Since the variable interpreted in this study is binary, the results of the logit model are also used in this article to verify reliability. To test hypothesis H1, the OLS model is specified as follows:

$$mismatch_i = \alpha_0 + \alpha_1 digital_i + X_i\alpha + \mu + \omega_j + \epsilon_i \quad (1)$$

$mismatch_i$ mismatch between education and job (*i – individual),*
$digital_i$ – level of digital skills, X_i – vector of control variables (age, education, experience, etc.), α_1 – key coefficient of the impact of digital skills on mismatch, α_0, α – coefficients for control variables, μ – year fixed effects, ω_j –

regional fixed effects, ε_i – standard error of the model. Formula 1 estimates the direct impact of an employee's digital skills (digital) on the risk of education-job mismatch (mismatch), controlling for individual factors (X), time (μ), and regional (ω_j) effects.

$$information_i = \beta_0 + \beta_1 digital_i + X_i\beta + \mu + \omega_j + \epsilon_i \tag{2}$$

information$_i$ – indicator of access to information (i – individual), β_1 – coefficient of the impact of digital skills on access to information, X_i – vector of control variables, β_0, β – coefficients for control variables, μ – year fixed effects, ω_j – regional fixed effects, ε_i – standard error of the model. Formula 2 tests the hypothesis of the information channel: how digital skills improve access to data (information), thereby reducing job mismatch.

$$work_i = \gamma_0 + \gamma_1 digital_i + X_i\gamma + \mu + \omega_j + \epsilon_i \tag{3}$$

work$_i$ – indicator of flexible employment (i – individual), γ_1 – coefficient for the impact of digital skills on access to flexible forms of employment, X_i – vector of control variables, γ_0, γ – coefficients for control variables, μ – year fixed effects, ω_j – regional fixed effects, ε_i – standard error of the model. Formula 3 analyzes the flexible employment channel: the role of digital competence in the transition to remote/project-based work (work), which adjusts mismatch. The overall objective of the models is to identify the mechanisms through which digitalization influences the labor market balance from the perspective of skills. Formulas (2)–(3) demonstrate the indirect effect mechanisms outlined in Formula (1).

To match supply and demand, workers spend significant time gathering information to find jobs and for employers to recruit qualified labor [25], which leads to short-term imbalances [26]. As a result, in 2014, labor market information emerged, which in turn contributed to short-term imbalances.

Digital skills can help workers achieve greater job flexibility. The creation of digital infrastructure has supported the digital development of traditional industries, and the computing capacity across various sectors has rapidly increased. Office software and other professional tools have become essential skills for workers. Improving computer literacy can help employees access more skilled and flexible job opportunities [27].

Based on the analysis above, the following hypotheses are proposed in this article:

H_1: Enhancing digital technology skills can help eliminate the mismatch between employees' academic qualifications and their job positions.

H_2: Improving digital skills can enhance the alignment between education and employment by reducing information asymmetry.

3. Materials and Methods

3.1. Study of Employees' Digital Skill Levels in the Context of Digital Transformation

Objective of the study: to assess how well employees' skills meet the requirements of digital transformation across various cities in Kazakhstan. The research was conducted in five cities: Astana, Almaty, Atyrau, Shymkent, and Akmola Region. A total of 1,102 respondents participated in the survey, selected randomly, with approximately equal representation from each city.

Data were collected using a structured online questionnaire distributed via the Google Forms platform. Respondents received a link to the survey, which they could complete at their convenience. Participants were divided into three categories: employees, employers, and the self-employed (excluding those who do not use the Internet in their work). The study involved staff from both public and private organizations across various sectors, including agriculture, industry, retail, services, and education.

The gender composition was balanced, with approximately half of the respondents being male. The average age of participants was 35 years. The survey data covered a wide range of basic enterprise-related information, including infrastructure, production and sales, competition, innovation and technology, financing, government-business relations, labor force, and performance outcomes. In this article, companies operating in the IT industry were excluded from the research sample. (Detailed data are presented in Table 1.)

Table 1.
Characteristics of the respondents.

Parameters		**Respondents**	
		Repeatability	**Percentage (%)**
Gender	Male	670	60.79
	Female	432	39.21
Age	from 20 to 30 years old	310	28.13
	from 31 to 40 years old	441	40.03
	from 41 to 50 years old	231	20.96
	from 51 to 60 years old	120	10.88
The level of education	Middle school	55	4.90
	Incomplete higher education	103	9.34
	Higher education	944	85.76
Type of work	Permanent	988	89.65
	Temporary	114	10.35

The survey was conducted using a 5-point Likert scale (from "strongly disagree" to "strongly agree"). The study analyzes respondents' perceptions of digital transformation and its impact on professional development, labor productivity, and workplace characteristics. The assessment was carried out across five key areas: labor market digitalization, development of competencies and skills, adaptation and training processes, perception of risks and challenges, and working conditions and organization.

3.2. Frequency Analysis

The survey was conducted using a 5-point Likert scale (from "strongly disagree" to "strongly agree"). The study analyzes respondents' perceptions of digital transformation and its impact on professional development, labor productivity, and workplace characteristics. The assessment was carried out across five key areas: labor market digitalization, development of competencies and skills, adaptation and training processes, perception of risks and challenges, and working conditions and organization.

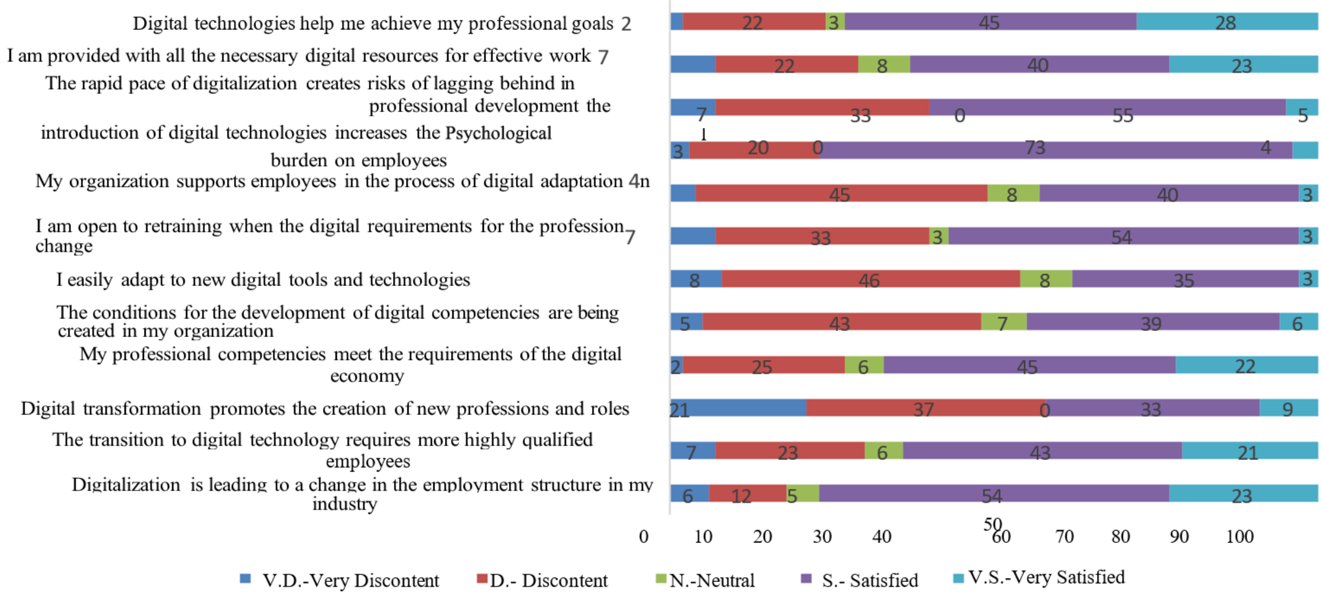

Figure 3.
Frequency Analysis of Respondents.

Overall digital maturity among respondents is high: more than 65% answered “Agree” or “Strongly agree” to 6 out of 12 statements. The most positive responses were related to the willingness to learn (87%) and awareness of the benefits of transitioning to digital technologies (73%). Problematic areas include adaptation to new technologies and poor organizational conditions for skills development (48–54% of respondents showed uncertainty). The lack of confidence in the emergence of new professions (58% of uncertain responses) indicates the need for informing and educating employees to drive real changes in the labor market (Figure 3).

According to the survey, respondents generally assess the impact of digitalization positively: over 70% stated that they strongly agree or agree (including the perception of digital technologies as tools for achieving goals and a willingness to acquire new digital skills). At the same time, about 54% of respondents experience difficulties adapting to new digital tools, and 48% believe their organizations are not sufficiently prepared to support the development of digital competencies. This indicates that support and personalized approaches to digital adaptation within companies need improvement. Despite recognizing the importance of continuous learning, 58% of respondents are not confident that digitalization leads to the creation of new professions, which may reflect an information gap and a lack of visible change in practice.

4. Results

For the empirical analysis, data from a questionnaire survey were used, in which respondents assessed the impact of the transition to digital technologies on professional development, working conditions, and perceptions of organizational and market factors. The initial dataset includes a dependent variable (R): an indicator reflecting the overall impact of the digital transition (e.g., successful adaptation, productivity growth, job satisfaction, etc.).
Independent variables (Table 2):

Group 1: Organizational factors (availability of upskilling programs, investment in digital transformation, managerial support);

Group 2: Functional characteristics (required education level, degree of digitalization of job functions); Group 3: Market and external factors (regional disparities in digital infrastructure, technological change);

Group 4: Qualification-job match and working conditions, including interactions between variables (skills supporting growth, lifelong learning skills, digital literacy).

The study employed a comprehensive quantitative approach: the collected data covered both internal (organizational and individual) and external (market and regional) determinants of change. Special attention was given to interactions between variables that reflect the conditions and consequences of digitalization. Regression models were applied with stepwise inclusion of factor blocks, which allowed for identifying key influencing variables and hidden effects.

The initial data consisted of employee survey responses reflecting their perceptions of digital changes, the level of organizational support, job characteristics, and market and regional conditions. Composite indicators and variable interactions ("Skill × Supports for Growth") were constructed, enabling the assessment of both direct and mediated effects on the dependent variable. A stepwise regression analysis was conducted, preceded by correlation checks and VIF calculations.

Table 2.
Correlation Analysis.

Parameters		Mean	S.D.	1	2	3	4	5	6	7	8
Gender	1	0.76	0.323	1							
Age	2	0.67	1.001	0.012*	1						
Level of education	3	1.34	1.344	0.127**	0.123**	1					
Work experience	4	1.41	0.526	0.002	0.024*	-0.021*	1				
Experience with digital technologies	5	5.37	0.117	0.023	0.021*	0.057*	0.301**	1			
Flexibility to learn / ability to adapt	6	2.63	0.423	-0.627	-0.117	0.220**	0.129**	0.456**	1		
Using digital skills	7	4.15	0.621	0.168**	0.149**	0.317**	0.340**	0.344**	0.567**	1	
Performance	8	3.92	0.231	-0.017	-0.140**	0.429**	0.169**	0.315**	0.651**	0.565**	1

Note: *: p<0.05, **: p<0.01.

The results of the correlation and regression analysis enable us to draw several important conclusions regarding the impact of organizational, professional, market, and interactive factors on the target variable (e.g., perception of digital changes, professional development, or labor productivity).

Table 3.
Results of multiple regression analysis.

Variables	Model 1 Standardized Coefficient β (t-statistics)	Model 2 Standardized Coefficient β (t-statistics)	Model 3 Standardized Coefficient β (t-statistics)	Model 4 Standardized Coefficient β (t-statistics)
Group 1. Organizational factors				
Availability of advanced training programs in the organization	0.011(3.133)	0.019(2.500)	0.019(0.704)	0.028(0.532)
Investing in digital transformation	0.008(0.302)	0.007(0.301)	0.003(0.129)	0.002(0.505)
Management support for the implementation of new technologies	0.018(3.345)	0.029(2.538)	0.033(0.549)	0.034(0.551)
Group 2. Characteristics of workplaces				
Education – Required digital and soft skills for the current position		0.044(1.219)	0.059(0.389)	0.076(0.661)
Skill – Level of digitalization of the workplace		-0.005(0.013)	-0.004(-0.012)	-0.001(-0.011)
Group 3. Market and external factors				
Regional differences in the level of digital infrastructure			0.345***(3.175)	0.369***(4.765)
Technological changes in the industry			0.061(1.018)	0.083(2.044)
Group 4. Factors of matching professional skills and organizational environment				
Job Fit / Education				0.213 (-2.009)
Job Fit / Supports for Individual Growth				0.771(0.611)
Skill – Job Fit				0.047(0.761)
Skill – Supports for Individual Growth				0.371***(4.075)
Adjusted R^2	0.061	0.077	0.190	0.245
F-statistic	28.016***	23.073***	15.821***	10.399***

Note: ***: p<.01.

Key quantitative results (Table 3):

Regression coefficients (β) and t-statistics are presented for each variable in the model. Significant effects are highlighted (typically at p<0.05 or p<0.01).

- The most significant predictors are regional differences (β ≈ 0.35–0.37, p<0.01) and the interaction term "Skill × SupportsGrowth" (β ≈ 0.37, p<0.01).
- Some variables showed a negative effect (Skill – level of workplace digitalization, β ≈ -0.001, p<0.05).
- The adjusted R^2 of the models indicates improved predictive power with the addition of new variables (ranging

from 0.061 to 0.245).
- All models are statistically significant according to the F-test ($p<0.001$).

Organizational variables, such as administrative support and the availability of professional development programs, have a significant impact at the early stages of model development (Models 1–2), but lose their statistical significance after the inclusion of external and interactional factors. This may indicate a mediating nature of their influence: these factors may indirectly affect the outcome by improving digital skills, motivating employees, or ensuring compatibility between tasks and competencies.

It would be advisable to conduct further mediation analysis or structural modeling (MWM) to clarify these relationships.

Job characteristics (educational and qualification requirements) proved insignificant in their direct effect, but the interaction between skill level and support for individual growth plays a significant role (0.371, $p < 0.01$), confirming the synergy hypothesis for this variable: digital skills have a meaningful impact only when there is an organizational environment that supports career development.

Regional differences in digital infrastructure have the most persistent and significant influence across all models, starting from Model 3. This result highlights the importance of the regional context in assessing digital maturity and readiness for change. It has practical implications for regional policymakers and employers operating under conditions of digital inequality.

Special attention should be given to the negative relationship between the variables "Skill" and "Level of workplace digitalization" (-0.001, $p < 0.05$). The negative contribution of this variable may suggest that a high level of digitalization in work processes causes stress or a sense of incompetence among employees who lack sufficient digital skills.

The results of the correlation and correlation matrix analysis indicate a moderate degree of multicollinearity among certain variables, particularly when considering interactions.

Centering variables before creating interaction terms and possibly using principal component analysis to generate composite predictors may improve model stability and interpretability.

Moreover, the weak correlation of some variables with the dependent variable does not imply their exclusion from the model; they may still be significant in the context of multivariate analysis, as confirmed in this case.

5. Discussion

Studies show that, compared to employees who do not work online, those who use the Internet generally receive higher wages after changing jobs [28, 29]. Other studies have also demonstrated empirical evidence of income differences [30-33].

With the development of the digital economy, upskilling workers in digital technologies has significantly alleviated employment issues and improved the alignment between employees' academic qualifications and job positions.

The digitalization of the labor market reveals and exacerbates the mismatch between education and required skills. A lack of skills becomes a barrier not only to productivity growth but also to employees' professional development.

Data confirm that adaptation to digital conditions will be fragmented and unstable without comprehensive reskilling policies and support measures.

The analysis indicates that there is an effective relationship between skills and job responsibilities, not only at the individual level but also at the organizational level. Access to training, support for career development, and family-oriented policies strengthen this alignment and enhance employee resilience in facing digital challenges.

Thus, digitalization requires a systematic approach to performance management within organizations. The results confirm that the alignment between skills and job content is a statistically significant indicator of employees' perception of digital changes and professional adaptation.

The effect was particularly strong in groups with high organizational support and access to learning resources. This highlights the importance of creating conditions that support the continuous development of skills relevant to the digital transformation of business processes.

6. Conclusion

The analysis results showed that the perception of digital transformation in the workplace largely depends on regional differences in infrastructure and the interaction between digital skills and support for professional development. The direct impact of regulatory factors is significant at the initial stage of model development but weakens when external and reactive variables are included, indicating an indirect influence. A negative correlation was found between the level of workplace digitalization and self-assessed skill levels, which may indicate difficulties employees face in adapting to new technologies.

The degree of alignment between skills and working conditions plays an important role only in the context of organizational support. Interaction variables demonstrate a synergistic effect by increasing the model's predictive power.

The R^2 value rises as the model complexity increases, confirming that additional factors were taken into account. Correlation analysis revealed the need to center variables and potentially apply dimensionality reduction methods to enhance model stability.

Thus, the study results indicate that the relationship between employees' skills and evolving job requirements is of primary importance in the digitalization era. The mismatch of skills has become a key factor limiting both employee productivity and adaptability.

This highlights the need for continuous updating of employability skills and systematic support from both employers and educational institutions.

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