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FULL LENGTH ARTICLE

The Impact of Digital Literacy, Automation, and Soft Skills on Employment Conditions of Non-Specialist Workers

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ABSTRACT

The main target areas of this article are to analyze the impact of the fast-growing digital economy on the labor market, as well as the rise in the number of under-skilled workers due to rapid changes in required skills and qualifications. Alongside foreign literature, the influence of automation, artificial intelligence, digital knowledge and platforms, and the "gig economy" are examined. A social survey covering more than one thousand employees from six different sectors was conducted to understand the extent of the growing number of unskilled and unemployed staff in the labor market of Uzbekistan. Various methods, such as econometrics, empirical models, and artificial intelligence, were implemented to analyze and correct some parts of this scientific research, with the exception of the main and econometric analysis. The formation of adaptable digital and soft competencies in the education system is a priority.

Keywords: Employees ▪ Digital economy ▪ Digital literacy ▪ Labor market ▪ Transformation of skills

1. INTRODUCTION

The digital economy has become a main part and a key driving force behind the modern economy. According to reports from the World Bank and the International Labour Organization (ILO), 30–40% of jobs in the labor market are at risk of automation. To prevent the consequences of this process, Uzbekistan is actively implementing a policy aimed at transforming the country into a digital center through the state-announced "Digital Uzbekistan 2030" strategy and related digital reforms. Specific goals include increasing the export of IT services to 5 billion US dollars and expanding electronic services in public administration. Current statistics also confirm these changes: the industry workforce (ICT sector) grew to 87,800 people in 2023, from approximately 62,200 people in 2020, indicating an expansion of jobs in the ICT sector and an increase in demand for digital skills. Internet and mobile coverage are also increasing.

The impact of digital transformation on the labor market is not only associated with an increase in the number of workers, but also with a qualitative reorganization of professions. This leads to specialists not finding work in their field and moving to other areas. The purpose of the article is to identify the main trends in the requirements for professions and skills in the digital economy.

2. LITERATURE REVIEW

Preventative methods have been implemented to decrease the number of under-skilled workers due to adaptation problems. Because of the digital economy and the popularization of digital knowledge, professions and skills have undergone major changes [1]. This area has been studied by various foreign scientists [2]; the cited literature also discusses ILO (2023). In particular, the World Bank has studied the opportunities and problems of the labor market as a result of digital transformation in its reports, and Schislyaeva and Saychenko have studied the importance of soft skills in the digital economy [3].

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Janine Berg and colleagues have studied the conditions and rights of online platform workers, as well as the quality of work [4]. Mark Graham, Isis Hjorth, Vili Lehdonvirta, and others have studied the income, social protection, and skills development of platform-economy and gig-economy workers [5]. Maria Jepsen and Jan Drahokoupil investigated labor demand, job polarization, and changing labor-market structures [6].

Some authors, such as Carl Benedikt Frey and Michael A. Osborne, have argued that the high rate of job loss is due to the creation of new tools and the burden of complementarity in occupations [7]. Frey and Osborne assessed the potential for computerization of occupations and argued that the impact of automation on production is a major motivation for employment in the workplace [8]. Some authors have developed an economic case for additional investment and the technological burden of automation, which helps support the demand for labor for the tools that automation replaces (Acemoglu, 2018; Restrepo, 2019).

3. METHODOLOGY

3.1 Data and Sample

A social survey was used as the main analytical method for this study. The survey was designed to shed light on the increasing share of unskilled workers in the labor market under the influence of the digital economy. About 1,200 respondents participated. Multiple AI platforms (ChatGPT and OpenAI) were implemented in some parts of the study to improve clarity, comprehension, and academic standards [9].

3.2 Variables and Measurements

To study the impact of the digital economy on non-specialist workers, variables such as labor-market conditions, digital literacy, soft skills, and automation were selected. These factors are intended to explain the increase in non-specialists in the labor market because of the transformation of professions under the influence of the digital economy. The model is linear, and the effect of variables x_1, x_2, and x_3 on the Y indicator is studied.

The independent variables are rated on a Likert scale from "very bad" to "very good." This increases the precision of econometric calculations and makes it easier to explain the impact of digital literacy, automation, and soft skills on non-specialists in the labor market.

3.3 Analysis and Results

The loss and transformation of professions are caused by a decrease in the number of workers performing simple, repetitive operations. This, in turn, is forcing specialists to change their specializations. New professions are also emerging, including data analysts, cybersecurity specialists, digital marketing managers, UX/UI designers, and IT developers. Along with technical skills, the importance of soft skills—creativity, communication, critical thinking, and problem-solving—is leading to a transformation of skills. This indicates the increasing importance of lifelong learning and the use of online platforms.

Descriptive statistics for the factors are presented in Table 1.

Table 1. Descriptive statistics on factors.

Variable	Obs.	Mean	Std. Dev.	Min	Max
cond	1120	4.125	0.792	2	5
digital	1120	4.063	0.848	1	5
auto	1120	3.759	1.128	1	5
soft	1120	3.054	1.626	1	5

The descriptive data indicate that while digitalization is widespread, disparities in skills acquisition remain notable, potentially influencing labor-market adaptation. We next analyze the correlation and determine the density of interconnection among the factors using pairwise correlation coefficients (Table 2).

Table 2. The correlation matrix.

Variables	(1)	(2)	(3)	(4)
(1) cond	1.000			
(2) digital	0.587	1.000		
(3) auto	0.434	0.510	1.000	
(4) soft	0.293	0.205	0.129	1.000

All relationships are positive, meaning improvements in one factor are generally associated with increases in others, though the strength varies from weak to moderate. It is important to understand multicollinearity between influencing factors. The Variance Inflation Factor (VIF) coefficients are used to check for multicollinearity (Table 3).

Table 3. Variance inflation factors.

Variable	VIF	1/VIF
Digital	1.390	0.720
Auto	1.350	0.739
Soft	1.040	0.957
Mean VIF	1.260	

Since all VIF values are well below the conventional threshold of 5, multicollinearity is not a concern in the estimated model. However, correlation coefficients only measure the degree of connection between economic indicators and cannot explain the causes of economic relations. Regression analysis provides an opportunity to assess the influence of factors affecting the resulting indicator. We therefore analyze digital literacy, the degree of workplace automatization, and the soft skills needed by employees through regression models (Table 4).

The regression results in Table 4 show that digital literacy has a strong positive and statistically significant effect on the employment conditions of non-specialist workers ($\beta = 0.548$, $p < 0.01$). A one-unit increase in digital literacy is associated with an average 0.55-point improvement in labor-market conditions. The model explains 34.4% of the variation in labor-market conditions ($R^2 = 0.344$), suggesting that digital competencies play a major role in shaping employment outcomes. The overall model is highly significant ($F(1, 1118) = 586.33$, $p < 0.001$), with Akaike (AIC = 2187.78) and Bayesian (BIC = 2197.83) information criteria.

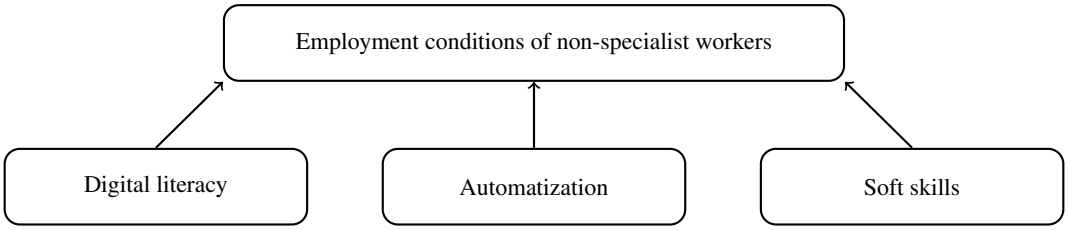


Figure 1. Factors affecting the employment conditions of non-specialist workers in the labor market.

Table 4. Pairwise regression results for employment conditions (Tables 4-a–4-c).

Model	Term	Coef.	St.Err.	t-value	p-value	95% CI	Sig.
4-a: Digital literacy	digital	0.548	0.023	24.21	0	[0.503, 0.592]	***
	Constant	1.900	0.094	20.24	0	[1.716, 2.084]	***
Mean dependent var = 4.125; SD dependent var = 0.792; R^2 = 0.344; observations = 1120							
F-test = 586.334; Prob > F = 0.000; AIC = 2187.782; BIC = 2197.825							
4-b: Automation	auto	0.304	0.019	16.09	0	[0.267, 0.342]	***
	Constant	2.981	0.074	40.14	0	[2.835, 3.126]	***
Mean dependent var = 4.125; SD dependent var = 0.792; R^2 = 0.188; observations = 1120							
F-test = 258.764; Prob > F = 0.000; AIC = 2426.833; BIC = 2436.875							
4-c: Soft skills	soft	0.143	0.014	10.25	0	[0.116, 0.170]	***
	Constant	3.689	0.048	76.51	0	[3.594, 3.783]	***
Mean dependent var = 4.125; SD dependent var = 0.792; R^2 = 0.086; observations = 1120							
F-test = 105.112; Prob > F = 0.000; AIC = 2559.371; BIC = 2569.413							

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The automation model demonstrates a positive and statistically significant impact on the employment conditions of non-specialist workers ($\beta = 0.304$, $p < 0.01$). However, its explanatory power ($R^2 = 0.188$) is considerably lower than that of digital literacy, indicating that automation is a less dominant determinant of job outcomes for employees working outside their field of specialization. The positive coefficient suggests that greater exposure to automation may improve working conditions through higher efficiency, technological support, and reduced manual workloads.

Soft skills, such as communication, teamwork, and adaptability, have a positive and significant relationship with labor-market conditions ($\beta = 0.143$, $p < 0.01$). Nevertheless, the explanatory power ($R^2 = 0.086$) is the lowest among the three models, implying that soft skills alone are not sufficient to predict working conditions effectively. The results highlight digital literacy as the most influential factor in improving labor-market conditions, followed by automation and soft skills. This finding underscores the centrality of digital competence in modern labor markets, especially in economies undergoing technological transformation.

We also perform a multifactor regression analysis of all independent variables with the outcome variable (Table 5).

The multifactor regression results demonstrate that digital literacy, automatization, and soft skills jointly exert a statistically significant influence on labor-market conditions. All coefficients are positive and highly significant ($p < 0.01$), indicating that improvements in each variable are associated with better labor-market outcomes. The model explains 39.8% of the variation in the labor conditions of non-specialist employees ($R^2 = 0.398$), improving on the single-factor models in Tables 4-a–4-c. The F-statistic ($F = 245.989$, $p < 0.001$) confirms the overall statistical significance of the model. The Akaike (AIC = 2095.52) and Bayesian (BIC = 2115.61) information criteria are lower than those of the single-variable models, implying a better model fit and higher predictive efficiency.

The estimated multifactor econometric model takes the following functional form:

$$Y_x = 1.65 + 0.43x_1 + 0.12x_2 + 0.08x_3. \quad (1)$$

Here, Y represents labor-market outcomes of non-specialist workers, x_1 denotes digital literacy, x_2 captures exposure to automation, and x_3 reflects soft skills. The estimated coefficients indicate that digital literacy is the most influential determinant of labor-market outcomes. A one-unit increase in digital literacy (x_1) is associated with an average increase of 0.43 units in labor-market outcomes, holding other factors constant. This highlights the role of digital competence in enabling workers to adapt to structural changes in the labor market, particularly those employed outside their field of specialization. Automation (x_2) also has a positive and statistically significant effect, increasing labor-market outcomes by 0.12 units. This suggests that greater exposure to automated processes may improve working conditions through higher productivity, reduced manual workload, and the creation of complementary tasks requiring new competencies. Soft skills (x_3), including communication, teamwork, and adaptability, contribute positively as well, albeit with a smaller magnitude (0.08 units). While their individual impact is weaker compared with digital literacy, soft skills remain essential for enhancing employability, especially in flexible and non-standard forms of employment. The constant term (1.65) reflects the baseline level of labor-market outcomes when all

Table 5. Calculated parameters of the multifactor econometric model.

Term	Coef.	St.Err.	t-value	p-value	95% CI	Sig.
digital	0.430	0.026	16.83	0	[0.380, 0.480]	***
auto	0.123	0.019	6.50	0	[0.086, 0.161]	***
soft	0.086	0.012	7.42	0	[0.063, 0.109]	***
Constant	1.651	0.093	17.67	0	[1.468, 1.835]	***
Mean dependent var = 4.125; SD dependent var = 0.792; R^2 = 0.398; observations = 1120						
F-test = 245.989; Prob > F = 0.000; AIC = 2095.524; BIC = 2115.609						

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

explanatory variables are held at zero, indicating that structural and institutional factors beyond the model also influence employment conditions. Overall, the model underscores that digital literacy plays a dominant role, while automation readiness and soft skills act as supporting factors. These results emphasize integrated workforce-development policies that prioritize digital-skills training, lifelong learning, and transferable competencies to reduce professional mismatch in the labor market.

4. CONCLUSION

Insufficient digital literacy, limitations in adaptability to automation, and weak soft skills significantly hinder the employability and productivity of the market workforce. This leads many non-specialist workers to face job insecurity and limited career opportunities. Addressing these challenges requires strengthening digital competencies and encouraging continuous professional development in accordance with labor-market demands. Another outcome is the creation of lifelong-learning opportunities and their relevance to the times. Digitalization will continue to be a game changer in the transformation of professions and skill requirements.

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