



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 is to analyze the impact of fast growing digital economy in the labor market, as well as the rise in the number of under-skilled workers due to the rapid changes in required skills and qualifications. Alongside with foreign literature attachments, the influence of automation, artificial intelligence, digital knowledge and platforms, and the “gig economy” are thoroughly examined. There is a social survey conducted covering more than one thousand employees from six different sectors in order to understand the extent of the growing number of unskilled and unemployed staff in the labor market of Uzbekistan. To deeply analyze and correct some units of this scientific research (with an exception in the main and econometric analysis part) various methods, such as econometrics, empirical model, artificial intelligence to name just a few has been implemented. In the end, it has been concluded that the formation of adaptable digital, soft competencies in the education system is a priority.

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

1. Introduction

It has already been proven practically that digital economy has already become a main part and a key driving force behind modern economy. According to reports from the World Bank and the International Labor 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; in particular, specific goals have been set, such as increasing the export of IT services to 5 billion US dollars and increasing the capacity of electronic services in public administration. Current statistics also confirm these changes: the industry workforce (ICT sector) is growing, reaching 87,800 people in 2023 from approximately 62,200 people in 2020 - which indicates an expansion of jobs in the ICT sector and an increase in demand for digital skills. At the same time, 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 (Manyika et al., 2017). This area has begun to be studied by scientists in a fundamental

way. The research examined the research and studies of various foreign scientists (Rimini & Spiezia, 2016; 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 in their studies (Schislyaeva & Saychenko 2022). Janine Berg and several scientists have also studied the conditions and rights of online platform workers, as well as the quality of work (Berg et al, 2018). Mark Graham, Isis Hjorth, Vili Lehdonvirta and others have studied the income, social protection and skills development of platform economy and gig economy workers (Graham, Hjorth & Lehdonvirta, 2017). Maria Jepsen and Jan Drahokoupillai investigated issues of labor demand, job polarization, and changing labor market structures (Jepsen & Drahokoupil, 2017). 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 (Acemoglu & Restrepo, 2018). Frey and Osborne have assessed the potential for computerization of occupation and argue that the impact of automation on production is a major motivation for employment in the workplace (Frey and Osborne, 2013). Some authors have developed an economic case for the additional investment and technological burden of automation, which helps to 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 has been taken as a main analytical method for this study. The survey was designed to shed light on the issue of the increasing share of unskilled workers in the labor market under the influence of the digital economy. About 1,200 respondents participated in it. To improve the clarity and comprehension along with its academic standards, multiple AI platforms (ChatGPT, OpenAI) has been implemented in some parts of the study.

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. That is, these factors should explain the reasons for the increase in non-specialists in the labor market because of the transformation of professions under the influence of the digital economy. Then our model is linear, and the effect of variables x_1 , x_2 , x_3 on the Y indicator is studied.

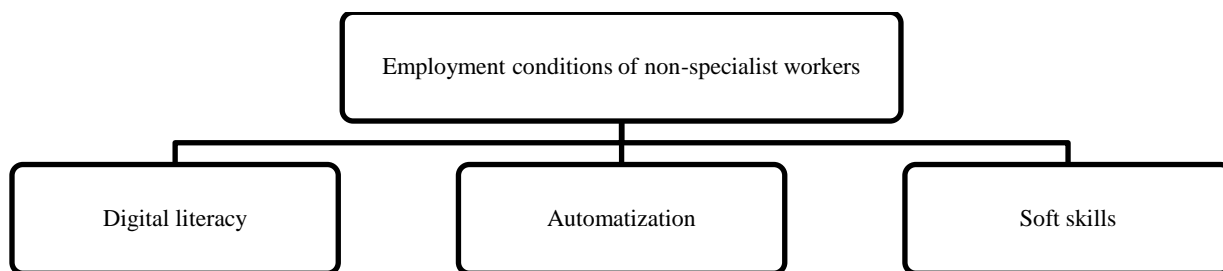


Figure 1. Factors which effecting on the employment conditions of non-specialist workers in labor market.

The independent variables are rated on a Likert scale from “very bad” to “very good”. This increases the level of precision in econometric calculations and makes them easier to calculate by explaining the impact of digital literacy, automation, and soft skills on non-specialists in labor market.

3.3 Analysis and Results

The loss and transformation of professions is 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 due to the entry into the labor market of professions such as data analysts, cybersecurity specialists, digital marketing managers, UX/UI designers, IT developers, etc. Along with technical skills, the importance of “soft skills” - creativity, communication, critical thinking, problem-solving skills - is leading to a transformation of skills. This indicates the increasing importance of lifelong learning and the use of online platforms.

Before, we conduct descriptive statistics on the factors. The obtained results are reflected in the table below.

Table 1: Descriptive statistics on factors.

Variable	Obs	Mean	Std. Dev.	Min	Max
cond	1120	4.125	.792	2	5
digital	1120	4.063	.848	1	5
auto	1120	3.759	1.128	1	5
soft	1120	3.054	1.626	1	5

From the data of Table 1, the descriptive data indicate that while digitalization is widespread, disparities in skills acquisition remain notable, potentially influencing labor market adaptation.

Firstly, we start the analyze the correlation analysis and determine the density of interconnection of each factor. To do it, we use the pair correlation coefficient and create a correlation matrix (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

From the data of Table 2, it is clear that 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. Therefore, we need to eliminate the problem of multicollinearity and move to the next stages of econometric modeling. Before, we can use another way to check the absence of multicollinearity between the influencing factors that caused multicollinearity by calculating VIF (Variance Inflation Factors) coefficients.

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	

The Variance Inflation Factor (VIF) test was conducted to assess potential multicollinearity among the independent variables (Table 3). Since all VIF values are well below the conventional threshold of 5, it can be concluded that multicollinearity is not a concern in the estimated model. However, since the correlation coefficient only measures the degree of connection between economic indicators, it cannot explain the causes of economic relations. This purpose is served by a special method known as regression analysis, and it provides an opportunity to assess the level of influence of the factors affecting the resulting indicator. Regression analysis starting with manage factors (provision of a workers digital literacy, the degree of automatization on work places and necessary soft skills for employees) to improve situation in labor market and full it with skilled employees rather than non-specialists (Table 4).

Table 4-a: The effect of digital literacy on employment conditions.

cond	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
digital	.548	.023	24.21	0	.503	.592	***
Constant	1.9	.094	20.24	0	1.716	2.084	***
Mean dependent var	4.125		SD dependent var		0.792		
R-squared	0.344		Number of obs		1120		
F-test	586.334		Prob > F		0.000		
Akaike crit. (AIC)	2187.782		Bayesian crit. (BIC)		2197.825		
*** $p < .01$, ** $p < .05$, * $p < .1$							

The regression results in Table 4-a show that digital literacy has a strong positive and statistically significant effect on the employment conditions of non-specialist workers ($\beta = 0.548$, $p < 0.01$). This indicates that a one-unit increase in the level of digital literacy leads, on average, to a 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 a relatively low Akaike (AIC = 2187.78) and Bayesian (BIC = 2197.83) information criterion, confirming good model fit.

Table 4-b: The effect of automatization on employment conditions.

cond	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
auto	.304	.019	16.09	0	.267	.342	***
Constant	2.981	.074	40.14	0	2.835	3.126	***
Mean dependent var	4.125		SD dependent var		0.792		
R-squared	0.188		Number of obs		1120		
F-test	258.764		Prob > F		0.000		
Akaike crit. (AIC)	2426.833		Bayesian crit. (BIC)		2436.875		
*** $p < .01$, ** $p < .05$, * $p < .1$							

Table 4-b demonstrates that automation has a positive and statistically significant impact on the employment conditions of non-specialist workers ($\beta = 0.304$, $p < 0.01$). However, the explanatory power of the model ($R^2 = 0.188$) 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 lead to improved working conditions for such employees, possibly due to higher efficiency, technological support, and reduced manual workloads.

Table 4-c: The effect of soft skills on employment conditions.

cond	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
soft	.143	.014	10.25	0	.116	.17	***
Constant	3.689	.048	76.51	0	3.594	3.783	***
Mean dependent var	4.125		SD dependent var		0.792		
R-squared	0.086		Number of obs		1120		
F-test	105.112		Prob > F		0.000		
Akaike crit. (AIC)	2559.371		Bayesian crit. (BIC)		2569.413		
*** $p < .01$, ** $p < .05$, * $p < .1$							

Table 4-c reveals that soft skills (e.g., communication, teamwork, 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.

It is clear seen from Table 4, the results highlight that digital literacy remains 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 considered a pairwise regression analysis of all independent variables with a non-independent variable. Lastly, we perform a multi-factor regression analysis of all independent variables with an independent on (Table 5).

Table 5: Calculated parameters of the multifactor econometric model.

cond	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
digital	.43	.026	16.83	0	.38	.48	***
auto	.123	.019	6.50	0	.086	.161	***
soft	.086	.012	7.42	0	.063	.109	***
Constant	1.651	.093	17.67	0	1.468	1.835	***
Mean dependent var	4.125		SD dependent var		0.792		
R-squared	0.398		Number of obs		1120		
F-test	245.989		Prob > F		0.000		
Akaike crit. (AIC)	2095.524		Bayesian crit. (BIC)		2115.609		
*** $p < .01$, ** $p < .05$, * $p < .1$							

The results of the multifactor regression model presented in Table 5 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 of these variables are associated with better labor market outcomes. The multifactor regression model explains 39.8% of the variation in labor conditions of non-

specialist employees ($R^2 = 0.398$), representing a substantial improvement compared to the single-factor models presented in Tables 4(A)–4(C). The F-statistic ($F = 245.989$, $p < 0.001$) confirms the overall statistical significance of the model, indicating that the included predictors jointly have a strong explanatory influence. Furthermore, 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.

According to the results reported in Table 5, the estimated multifactor econometric model takes the following functional form:

$$Y_x = 1.65 + 0.43x_1 + 0.12x_2 + 0.08x_3$$

where 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. Specifically, 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 finding highlights the critical role of digital competence in enabling workers to adapt to structural changes in the labor market, particularly for those employed outside their field of specialization. Automation (x_2) also exerts 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 to 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 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 in improving labor market outcomes for non-specialist workers. These results emphasize the importance of integrated workforce development policies that prioritize digital skills training, lifelong learning, and the development of transferable competencies to reduce professional mismatch in the labor market.

4. Conclusion

The insufficiency of digital literacy, limitations in adaptability to automation, and weak soft skills significantly hinder the employability and productivity of the market workforce. This, in turn, is leading to many non-specialist workers facing 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 creating lifelong learning opportunities and its relevance to the times. This is mainly because digitalization will continue to be a game changer in the transformation professions and skill requirements.

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