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THE IMPACT OF MODERN TECHNOLOGIES ON EMPLOYMENT AND UNEMPLOYMENT IN ECONOMIC THEORY AND ECONOMIC PRACTICE[1]

EKONOMİ TEORİSİNDE VE EKONOMİ PRATİĞİNDE MODERN TEKNOLOJİLERİN İSTİHDAM VE İŞSİZLİK ÜZERİNDEKİ ETKİSİ

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ABSTRACT

The aim of the paper is to identify changes in the labour markets resulting from the use of new technologies. The basis for the analysis are theoretical and empirical findings in economic theory and data about the development of new technologies and their employment effects. The article shows how the views of economic theory on the impact of new technologies on the labor market have developed, starting from classical economics until recent times. In particular, views were highlighted that saw the effect of displacing the labor force and the effect of creating new jobs. The analysis indicates that application of the task-based approach to study labour demand enables better identification of transition channels of modern technology on the size and structure of labour demand. In the empirical analysis of the paper, panel causality test was conducted with data for the period 2000-2023 for 11 Central and Eastern European (CEE) countries. The empirical research did not confirm the alarmist predictions about the possibility of high technological unemployment as a result of technical progress. However, changes in the structure of labour demand are evident. According to the causality test results, technological development appears to be particularly associated with total employment, youth employment and youth unemployment.

Keywords: Modern technologies, Employment, Unemployment, Labor Market.

JEL Codes: O33, E24, B23

ÖZET

Bu çalışmanın amacı modern teknolojik gelişmeler ile birlikte işgücü piyasasında oluşan değişiklikleri incelemektir. Bu kapsamda literatürde yer alan teorik ve ampirik bulgulara dayanılarak modern teknolojilerdeki gelişmelere ve bunların işgücü piyasasına etkilerine yer verilmiştir. Yeni teknolojilerin işgücü piyasası üzerindeki etkilerine yönelik görüşler klasik iktisadi düşünceden günümüze kadar farklılaşmakta ve işgücü yapısındaki değişiklikler ile yeni işler yaratılmasının etkilerini savunan görüşlerin literatürde mevcut olduğu anlaşılmaktadır. Diğer yandan literatürde konuya yönelik yapılan analiz bulguları modern teknolojideki gelişmelerin işgücü talebinin büyüklüğünü ve yapısını etkilediğini de göstermektedir. Bu çalışmada ampirik bir analize de yer verilerek 11 Orta ve Doğru Avrupa ülkesi için 2000-2023 dönemine ait veriler ile panel nedensellik testi gerçekleştirilmiş ve teknolojik gelişmelerin istihdam ve işsizlik ile nedensellik ilişkisi araştırılmışır. Elde edilen bulgular teknik bir ilerlemenin sonucu olarak yüksek teknolojik işsizlik olasılığı hakkındaki öngörüleri doğrulamakla birlikte işgücü talebinin yapısındaki değişikliklere açık olduğunu göstermektedir. Çalışmanın nedensellik testi bulguları ele alınan pek çok ülkede teknolojik gelişmelerin toplam istihdam, genç istihdam ve genç işsizliği ile nedensellik ilişkisine sahip olduğunu göstermektedir.

Anahtar Kelimeler: Modern teknolojiler, İstihdam, İşsizlik, İşgücü Piyasası.

JEL Kodları: O33, E24, B23

[1] This study is an expanded version of the study titled "The Impact of Modern Technologies on Employment and Unemployment in Economic Theory And Economic Practice " which was presented as an abstract at the 1st International WriteTec Congress on Social and Health Sciences in the Age of Artificial Intelligence.

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INTRODUCTION

In the first decades of the 21st century, labor markets face a number of challenges. These challenges include, first of all, modern technologies that increasingly impact economies and labor markets. The current technological revolution is characterized by an increasing degree of automation and, more recently, the use of Artificial Intelligence (AI) and Machine Learning. It is also reflected in the increasing number of industrial robots used in the economy.

The basic aim of this study is to present changes in employment and unemployment caused by the use of modern technologies, which have been proposed in economic theories and which can be observed in economic practice. The basis of the analyses carried out are primarily theoretical findings and results of empirical research in economic literature and trends occurring in reality in the field of modern technologies and contemporary labor markets.

The order of considerations in the article is as follows. Part 1 is focused on the impact of modern technologies on the level of employment and unemployment in economic theory, while part 2 presents new technologies and changes in employment structure on changes in the employment structure, part 3 contains trends in the development of modern technologies and some of their consequences on contemporary labor markets. Lastly, part 4 includes panel data analysis and findings, part 5 draws conclusions from the analyses performed.

1. MODERN TECHNOLOGIES AND THE LEVELS OF EMPLOYMENT AND UNEMPLOYMENT

In the analyses of the impact of technological changes (technical progress) on employment and unemployment undertaken in economic theory, two main directions can be distinguished: the impact on the size of employment and unemployment and the impact on the structures of these categories. Both directions of analysis have already a history in economics, and especially the first direction of research was and still is accompanied by strong controversies.

1.1. Theoretical hypotheses

Already in the times of classical economics, there were different views on the effects of the use of machines on the situation on the labor market. Adam Smith emphasized the beneficial consequences of the use of machines (Smith, 1954, pp. 101-104 and 435), while David Ricardo put forward the view that the use of machines tends to reduce the demand for workers and create an "excess population" (Ricardo, 1957, p. 454). Using modern terminology, it can be said that Ricardo saw the effect of displacing labor as a result of the use of machines (Ricardo, 1957, p. 457). It can be assumed that Ricardo accepted the view that technological unemployment arises as a result of technical progress.

The dispute over the effects of technological progress on employment and unemployment was also present in later economic investigations. In R. Solow's neoclassical model of economic growth, technical progress was treated as an important factor in production growth (Tokarski, 2005, pp. 20-27), while J. Schumpeter (1934) drew attention to product and process innovations that had an impact on employment and unemployment. He saw product innovations as a source of job creation as a result of technical progress, and process innovations as a "creative destruction" of jobs. Although representatives of neoclassical economics noticed the displacement of labor from the production process by technical progress, they strongly emphasized mechanisms compensating for the decline in employment in a free market economy (Vivarelli, 2007) and believed in the beneficial properties of technical progress, also on the labor market.

This faith began to be increasingly questioned by the experience of labor markets, as well as the development of Keynesianism, which was critical of the achievements of neoclassical economics. John Maynard Keynes (Keynes, 1931) predicted that although new technologies would ensure a constant increase in per capita income in the 20th century, they would also result in technological unemployment resulting from the replacement of people by machines. The vision of the "end of work" presented by J. Rifkin (2001) has gained great popularity. This work opened the field to a broader theoretical debate on the impact of modern technologies on the labor market, which developed at the beginning of the present century. David H. Autor, Daron Acemoglu and Pascual Restrepo play important roles in this debate.

The concept of the task approach in the analysis of employers' decisions regarding the demand for labor was important for the development of this debate (Autor, Levy & Murnane, 2003; Acemoglu & Restrepo, 2018). The essence of this concept is the statement that manufactured products are the result of a combination of specific tasks performed by factors of production, in particular by labor and capital. Some tasks performed by the labor force can be automated through the use of modern technology, while others cannot. Therefore, when modern technologies are implemented, some tasks previously performed by the labor force begin to be performed by capital, the so-called displacement effect, which results in the replacement of labor by machines and a reduction in demand for labor and employment (Acemoglu & Restrepo, 2018; Acemoglu & Restrepo, 2019). In addition to the displacement effect, the authors of the analysed concept note a number of mechanisms compensating for the decline employment. This is primarily about the effects of productivity and labor reabsorption (in the original - reinstatement) (Acemoglu & Restrepo, 2019), which increase the demand for labor.

Thus, some effects, especially the displacement effect, work towards reducing the demand for labor, while others, especially the effects of productivity and the creation of new tasks (reinstatement effect) , increase the demand for labor. The authors of the discussed concept do not clearly predict the direction of changes in the demand for labor under the influence of new technologies, but they tend to believe that in the future the effects of displacement may dominate the compensatory effects, as a result of which technological unemployment may arise, while the demand for labor and the level of employment may decline. (Acemoglu & Restrepo, 2019).

1.2. Empirical findings

The problem of the impact of modern technologies on the development of employment and unemployment has been repeatedly addressed in empirical research. In their widely cited work, Frey and Osborne (2017) attempted to estimate the vulnerability of employment to computerization in the United States economy. As a result, they found that 47% of all workers in the US economy work in jobs where humans could be replaced by computers within the next 10-20 years. From this they concluded that there is a real possibility of technological unemployment in the American economy in the near future.

Frey and Osborne's estimates were heavily criticized. Arntz, Gregory, and Zierahn (2016) conducted their own assessments of the risk of workplace automation in 21 OECD countries. These estimates show that the risk of automation is significantly lower, as it amounts to, among others: 6% of jobs in Korea, 7% in Poland, 9% in the USA and 12% in Austria (Arntz, Gregory & Zierahn, 2016). On this basis, they concluded that the use of new technologies does not pose a risk of technological unemployment, but the risk of automation is relatively high when performing manual activities.

A number of empirical studies were also conducted by D. Acemoglu and P. Restrepo. analysing the evolution of labor demand in the USA after World War II, they observed a slowdown in the growth of labor demand after 1990, and even stagnation after 2000. They stated that further automation will rather reduce the role of labor in production processes (Acemoglu & Restrepo, 2019).

The presented short review of empirical research shows that previous alarmist predictions about the possibility of high technological unemployment as a result of the use of modern technologies have not been confirmed in most studies. Most studies, however, noted a slowdown in growth and even stagnation of labor demand under the influence of new technologies, which suggests the possibility of negative trends in employment changes in the future.

2. NEW TECHNOLOGIES AND CHANGES IN EMPLOYMENT STRUCTURE

2.1. Theoretical hypotheses

Research on the impact of modern technologies on changes in employment structures also has a history in economics. Initially, they focused on changes in employment structures by sectors and industries, then by qualifications and occupations, and recently by tasks.

The first interesting comments on changes in the employment structure across sectors can be found in Adam Smith, who saw the need to move the labor force from agriculture to industry and then to trade in the process of increasing the country's wealth, which implied changes in the employment structure according to economic sectors. He treated these changes as the result of the "natural course of things", related to changes in the structure of consumption (Smith, 1954, vol. I, pp. 215-230 and 456-487).

Similar regularities related to the movement of labor in economic development from agriculture to industry and then to trade were noticed by F. List, who distinguished development stages based on the degree of development of individual fields of activity, including: agricultural stage, agro-industrial stage and agro-industrial-commercial stage. In F. List, the idea appears that the movement of labor from agriculture to industry and then to trade is the result of technical progress displacing labor from agriculture (List, 1922, pp. 63, 215 and 246).

The fundamental role of technical progress in shaping changes in the three-sectoral employment structure was emphasized by Jean Fourastie. While examining the process of economic evolution of societies, he drew attention to the tendencies of a decline in the share of agricultural employment, an increase and then decline in the share of industrial employment, and a continuous increase in the share of service employment along with economic development. Fourastie saw the reasons for these transformations in the impact of technical progress, which displaces labor from individual sectors with unequal force, because the dynamics of technical progress and the increase in labor productivity in the agricultural sector are moderate, in the industrial sector they are strong, and in the service sector they are weak or non-existent (Fourastie, 1954, pp. 126-137; Fourastie, 1972, p. 185).

At the end of the 20th century, research on changes in employee qualification structures became an important direction in the analysis of changes in employment structures under the influence of modern technologies. A number of arguments were highlighted in favour of increasing the share of highly qualified employees in this situation, primarily that highly skilled employees are the creators of these technologies and, moreover, they are necessary to operate the implemented technologies (Cahuc and Zylberberg, 2004, pp. 588-590; Bosworth, Dawkins and Stromback, 1996, pp. 143-146). The dominant theoretical concept that explained changes in the skill structure of employment was the theory of technical change favouring high skills (SBTC - Skill-Biased Technical Change), which assumed a shift in labor demand towards positions requiring relatively high skills.

At the beginning of the 21st century, the concept of Routinization-Biased Technical Change (RBTC) became more popular in economic literature, and was developed on the basis of a task-based approach to labor demand (Autor, Levy & Murnane, 2003). In this concept, the structure of employees is analysed not through the prism of professions, but through the tasks performed. These tasks are classified into non-routine groups (analytical, personal and manual) and routine groups (cognitive and manual). According to this concept, automation should replace routine tasks (both manual and cognitive), but should be complementary in the case of analytical and personal non-routine tasks.

2.2. Empirical findings

Empirical analyses for highly developed countries indicate that changes in the structure of labor demand are consistent with the RBTC hypothesis, i.e. the implementation of computers and robots reduces the demand for employees performing routine tasks (Acemoglu & Autor, 2011; Goos & Manning, 2007).

Slightly different results were obtained when examining a similar problem in the transformation countries of Central and Eastern Europe. It turned out that in these countries, automation does not lead to a decrease in demand for employees performing routine cognitive tasks, but on the contrary - it leads to an increase in demand (Gajdos, Arendt, Balcerzak & Pietrzak, 2020; Hardy, Keister & Lewandowski, 2018). This was explained by the relatively low degree of automation, the increase in the level of schooling in society (Arendt & Grabowski, 2019), as well by the low level of wages and labor costs in these countries.

3. TRENDS IN THE DEVELOPMENT OF MODERN TECHNOLOGIES AND LABOR MARKETS

The place of modern technologies in human life is becoming more and more evident every passing day. Modern technological developments in many areas from agriculture to industry, from education to health, from labor markets to energy markets make life easier and improve the lives of societies. New technologies that show their effects in many areas of the economy can also shape the labor market, and in this context, total employment and total unemployment, as well as youth employment and youth unemployment, can be affected by technological developments.

In this part of the study, current developments in modern technology and employment and unemployment, which are important elements of the labor market, are included. A recent report prepared by the World Economic Forum (2024) included the Top 10 Technologies of 2024 and developments in industries providing funding in technological areas. In line with this report, some industries and the amount of funding provided are listed in the table 1 below.

Table 1: Leading-edge industries

Leading-edge industries				
Industries with the most funding in integrated sensing and communication from 2021-2023				
Internet ($3.9 billion)	Electronics ($2.4 billion)	Mobile and telecommunications ($1.2 billion)	Computer hardware ($412 million)	Software ($250 million)
Industries with the most funding in AI for scientific discovery from 2021-2023				
Internet ($66.5 billion)	Software ($24.1 billion)	Healthcare ($10.3 billion)	Computer hardware ($4.3 billion)	Industrials ($4.2 billion)
Industries with the most funding in privacy-enhancing technologies from 2021-2023				
Internet ($5.1 billion)	Software ($1.7 billion)	Electronics ($1.5 billion)	Healthcare ($429 million)	Industrials ($189 million)

Source: World Economic Forum (2024).

There is a rapid improvement in technological developments prepared to improve the current situation of the world. As can be seen from **t**able 1, funds related to the internet in the leading-edge industries, are quite high. In the 2021-2023 period, the areas with the highest funds after the internet were observed as software, electronics, healthcare, mobile and telecommunications, computer hardware and industrials.

As United Nations (2024) said, modern technological developments, especially seen in the last twenty years, bring new transformations in societies. With these new transformations, for example, artificial intelligence-supported technologies in the health sector easily detect various diseases and help save lives. Virtual learning environments are being successfully created in the field of education and distance learning methods are developing every day. On the other hand, access to public services is becoming easier and bureaucratic procedures can be reduced through blockchain-supported systems. However, it is still not possible to say that everyone benefits equally from these developments in modern technologies. Especially women, the elderly, disabled people and those who are in minority groups, the poor and those living in remote areas can fall behind in modern technological developments. Globally, the proportion of women using the Internet lags behind that of men (12% lower). This gap is narrowing in many regions between 2013 and 2017 period, and widened from 30% to 33% in the least developed countries.

The rates of individuals using the internet are used in many studies as an important variable for understanding modern technological developments and the situation of countries is monitored with this data expressing information communication technologies. This study also focuses on the rates of individuals using the internet in CEE countries and attempts to explain the situation of countries in information communication technologies with this rate. For this reason, here are individuals using the internet rates of CEE Countries by year. This indicator is presented in the figure 1 below.

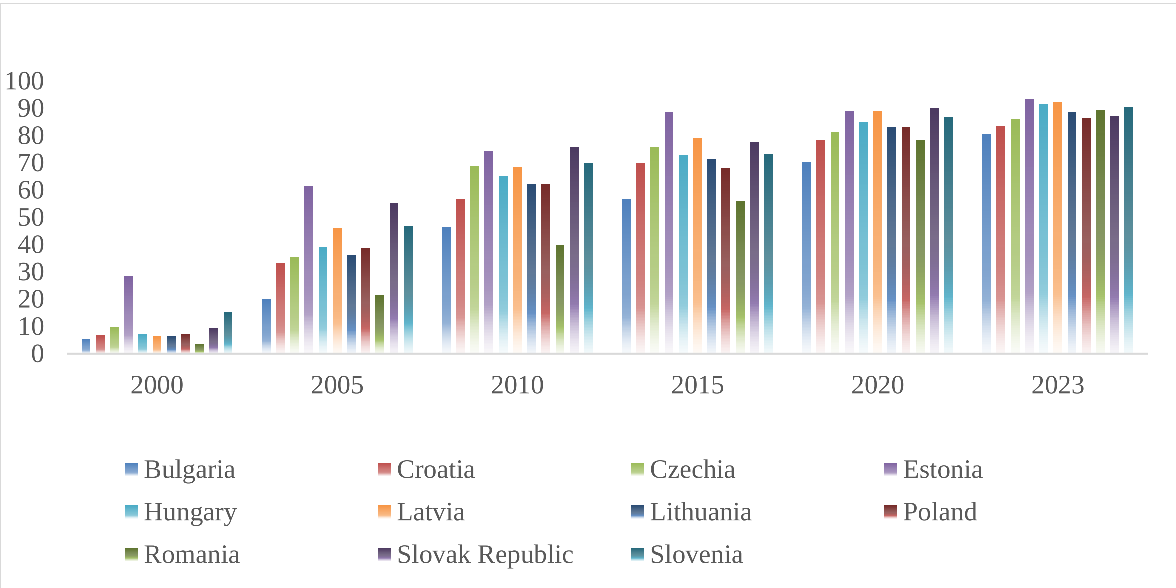

Figure 1: Individuals Using the Internet Rates of CEE Countries, 2000-2023 (% of population)

Source: World Bank (2024).

As can be seen in Figure 1, there is a significant development in the number of individuals who use the internet in 2020 and 2023 compared to 2020. When this graph, which shows individuals using the internet rates of CEE Countries (% of population), is examined in detail, it is understood that Estonia, Latvia and Hungary have the highest rates, respectively, while Bulgaria, Croatia and Czechia have the lowest rates. Considering that the internet use variable is an important measure of information and communication technologies, it can be considered that it shows the developments of the countries in this area. However, of course, internet use is not the only variable representing information and communication technologies, and it may also be useful to examine other technological developments, research in R&D and patents applications in countries.

Considering that technological developments in countries deeply affect the structure, economic and social dynamics of the labor market, it can be stated that changes in employment type and occupational preferences, skill areas, productivity and income structure are inevitable. In this regard, Graetz, Restrepo, and Skans (2022) said that technological developments actually bring different types of skills to the labor market. These authors state that this situation has also occurred quite rapidly with modern technologies such as machine learning and robotics in recent years. Indeed, in the last 40 years, technological developments have brought significant changes to the wage and occupational structures of the economy, systematic changes have occurred in the types of skills demanded by companies, and decreases have occurred in the share of income falling to the labor force. On the other hand, the labor market has a dynamic structure and if the technological developments are not adapted, the unemployment rate increases especially among the youth in the labor market and insufficient employment may occur. As Atalay et all (2018) emphasize, the use of information and communication technologies is becoming more important. Especially with the recent developments in the field of software, the rate of time spent by employees using information and communication technologies has increased significantly in the last half century and this shows the importance of modern technologies in the labor market.

Since this study examines the impact of modern technological developments on employment and unemployment and CEE countries are selected as a sample, employment and unemployment developments in these countries are also included. The figures below present total and youth employment data and total and youth unemployment data for 2023.

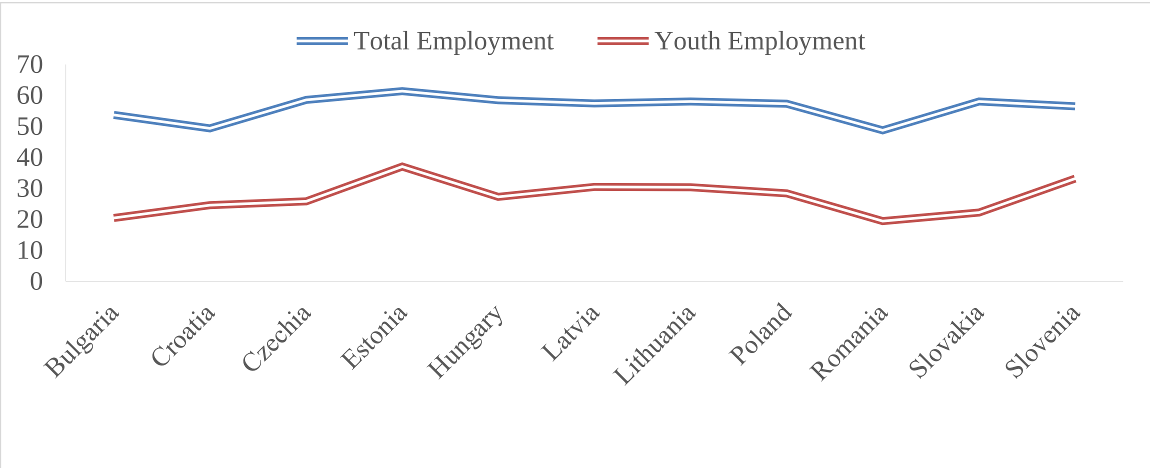

Figure 2: Total Employment Rates and Youth Employment Rates of CEE Countries, 2023 (%)

Source: World Bank (2024).

According to data from the World Bank (2024), the highest total employment to population ratio (15+) (modelled ILO estimate) in 2023 appears to be in Estonia (61.3 %). In terms of total employment, Estonia is followed by the Czech Republic (58.5 %), Hungary (58.4 %), and Lithuania (58.1 %). The ranking changes slightly in youth employment. When looking at employment to population ratio, (ages 15-24) (modelled ILO estimate), Estonia is again the first country, followed by Slovenia, Latvia and Lithuania, respectively.

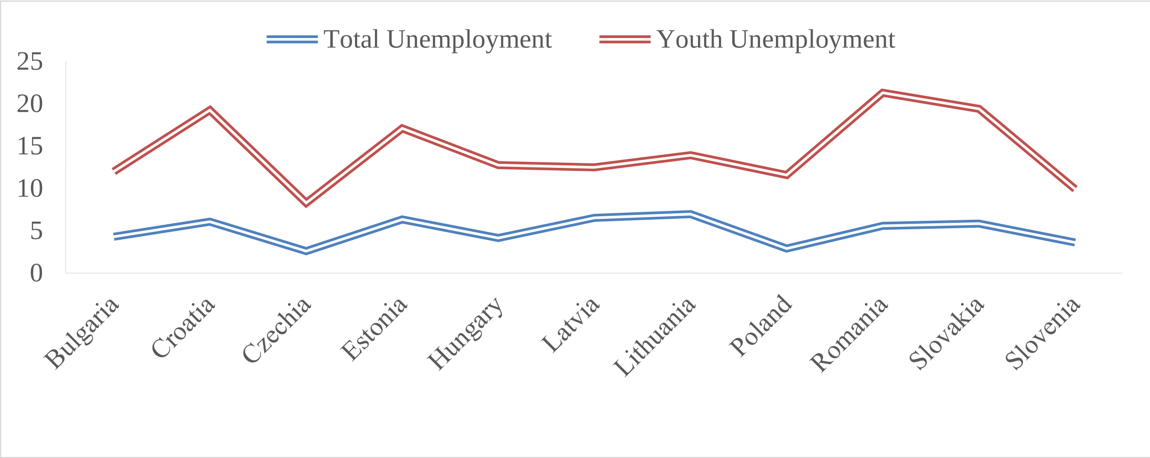

Figure 3: Total Unemployment Rates and Youth Unemployment Rates of CEE Countries, 2023 (%)

Source: World Bank (2024).

In this study, the World Bank's unemployment, total (% of total labor force) (modelled ILO estimate) data were used to examine the developments in total unemployment and youth unemployment in the countries considered. When the countries are evaluated in terms of total unemployment, while Lithuania (6.9 %) and Latvia (6.5 %) have the highest total unemployment rates in 2023, Czechia (2.5 %) and Poland (2.9 %) have the lowest total unemployment rates. On the other hand, the data show that the highest youth unemployment rates in 2023 are in Romania (21.3 %), Slovakia (19.4 %), Croatia (19.2 %) and Estonia (17 %), while the lowest youth unemployment rates are in Czechia (8.2 %) and Slovenia (9.9 %).

4. PANEL DATA ANALYSIS AND FINDINGS

In this part of the study, the causality relationship between employment-unemployment and technological development was analysed for 11 Central and Eastern European (CEE) Countries (Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia) using data from 2000 to 2023. The time period was determined according to the availability of data. The study focused on the relationships between total employment-total unemployment, as well as youth employment-youth unemployment, and technological development. The data set used in the econometric analysis for the period 2000-2023 for 11 CEE countries is presented in the table 2 below.

Table 2: Full Description of Variables

Variables	Code of Variables	Description of Data
Total Employment	TEM	Employment to population ratio, 15+, total (%) (modeled ILO estimate)
Total Unemployment	TUN	Unemployment, total (% of total labor force) (modeled ILO estimate)
Youth employment	YEM	Employment to population ratio, ages 15-24, total (%) (modeled ILO estimate)
Youth unemployment	YUN	Unemployment, youth total (% of total labor force ages 15-24) (modeled ILO estimate)
Technology	TEC	Individuals using the Internet (% of population)

Source: World Bank (2024).

Within the study, the total employment rate is defined as EM and means employment to population ratio, 15+, total (%) (modelled ILO estimate), the total unemployment rate (UN) is defined as unemployment, total (% of total labor force) (modelled ILO estimate), youth employment rate (YEM) shows employment to population ratio, ages 15-24, total (%) (modelled ILO estimate), the youth unemployment rate (YUN) is the number of the total youth unemployment (% of total labour force ages 15-24) (modelled ILO estimate) and technological development is defined as TEC and means individuals using the internet (% of population)[1]. All data have been extracted from World Bank's (2024) Data Bank and the following 4 models were created with these data.

Models

$$Model\ 1: TEM_{it} = \delta_{1i} + \delta_{2i} TEC + \varepsilon_{it} \quad (1)$$

$$Model\ 2: TUN_{it} = \alpha_{1i} + \alpha_{2i} TEC + u_{it} \quad (2)$$

$$Model\ 3: YEM_{it} = \beta_{1i} + \beta_{2i} TEC + \mathrm{p}_{it} \quad (3)$$

$$Model\ 4: YUN_{it} = \vartheta_{1i} + \vartheta_{2i} TEC + \mu_{it} \quad (4)$$

In equations (1), (2), (3) and (4), i stands for the countries (i=1, 2, . . . ,11), t denotes time period (t=2000, 2001, 2002, . . ., 2023), $\delta_{1i}, \alpha_{1i}, \beta_{1i}$ and ϑ_{1i} are constant terms, $\delta_{2i}, \alpha_{2i}, \beta_{2i}$ and ϑ_{2i} are, respectively, the parameters of technological developments that express the effect to total employment, total unemployment, youth employment, and youth unemployment.

[1] In many studies in the literature, this variable has been used as an index of modern technology or technological development. Therefore, it was preferred in this study.

As can be understood from the models presented above, the first panel data model focuses on the causality relationship between total employment and technological development, the second panel data model is created to determine the causality relationship between total unemployment and technological development, the third panel data model is created to determine the causality relationship between youth employment and technological development, and the fourth panel data model is created to determine the causality relationship between youth unemployment and technological development.

These four models which used in this study, are based on the bootstrap panel Granger causality test by Kònya. This bootstrap panel Granger causality test has some advantages when we compare it with the other panel causality tests: These advantages can be listed as follows;

- With this method, there is no need to test the stationarity of the variables or the cointegration relationship between the variables before starting the causality test.
- This test allows for cross-sectional dependence, so it is considered to be more realistic.
- In this test, panel heterogeneity is taken into consideration. In other words, results for each country are obtained and thus, it allows countries to be compared.

This test was preferred in this study due to these advantages. The test is carried out in two stages: in the first stage, cross-sectional dependence and panel heterogeneity (homogeneity) are investigated. In the second stage, the panel Granger causality estimate for each country is performed using the seemingly unrelated regression (SUR) method.

In today's world, the dependency between countries is quite high and an economic change (development or stagnation) occurring in one country can affect other countries. Therefore, taking into account the cross-sectional dependency is quite important and necessary for panel econometric analyses. When this situation is taken into account, the consistency level of the estimates made will be high (Pesaran, 2004). One of the test statistics to be used when testing cross-sectional dependency is the CD_{LM1} test proposed by Breusch & Pagan (1980) and this test is expressed as follows:

$$CD_{LM1} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{5}$$

In this CD_{LM1} test, the null hypothesis (H_o) states that there is no cross-sectional dependence. The alternative hypothesis (H_1) emphasizes that there is cross-sectional dependence for at least one pair. The hypotheses of this test are expressed as follows:

$H_o = cov(u_{it}, u_{kt}) = 0$ for all t and $i \neq t$)

$H_1 = cov(u_{it}, u_{kt}) \neq 0$ for at least *one pair of* $i \neq t$).

In the equation (5), $\hat{\rho}_{ij}$ means the pair-wise correlation coefficient of the residuals of ordinary least square forecasts for each i. The CD_{LM1} statistic is generally used to test cross-sectional dependence when $T \rightarrow \infty$ and N is constant, (i.e. T > N).

But if N is high in a model, it means that the power of the LM statistic decreases and, in this case, the CD_{LM2} and CD tests suggested by Pesaran (2004) is always used. Statistics of these tests are stated as indicated in the equations (6) and (7);

$$CD_{LM2} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T\hat{\rho}_{ij}^{2} - 1) \tag{6}$$

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \tag{7}$$

However, sometimes these tests may also fail to reject the H_o hypothesis and therefore the CD_{LMadj} test suggested by Pesaran, Ullah, and Yamagata (2008) can be used. The equation (8) for the bias-adjusted LM statistic is expressed as follows;

$$CD_{LMadj} = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \frac{(T-k)\hat{\rho}_{ij}^{2} - \mu_{Tij}}{\sqrt{v_{Tij}^{2}}} \tag{8}$$

In this equation (8), μ_{Tij} and v_{Tij}^{2} are, respectively, the mean and the variance of (T-k) $\hat{\rho}_{ij}^{2}$ as suggested by Pesaran, Ullah, and Yamagata (2008). Based on all this information, cross-sectional dependence was tested for each test statistic and the results obtained are presented in the table 3 and table 4 below.

Table 3: Cross-sectional Dependence Test Results (Based on variables)

	EM		**UN**		**YEM**		**YUN**		**TEC**	
	Stats.	Prob.	Stats.	Prob.	Stats.	Prob.	Stats.	Prob.	Stats.	Prob.
CD_{LM1}	83.07*	0.00	78.91**	0.01	46.42	0.78	136.78*	0.00	89,58*	0.00
CD_{LM2}	2.67*	0.00	2.28**	0.01	-0.81	0.20	7.79*	0.00	3.29*	0.00
CD	0.53	0.29	-3.06*	0.00	-2.83*	0.00	-1.12	0.13	-2.59*	0.00
CD_{LMadj}	25.52*	0.00	15.32*	0.00	13.97*	0.00	40.16*	0.00	9.79*	0.00
Notes: * and ** denote the significance for at 0.01 and 0.05 levels, respectively										

Table 4: Cross-sectional Dependence Test Results (Based on model)

	Model 1		Model 2		Model 3		Model 4	
	Stats.	Prob.	Stats.	Prob.	Stats.	Prob.	Stats.	Prob.
CD_{LM1}	121.25*	0.00	63.33	0.20	98.43*	0.00	83.43*	0.00
CD_{LM2}	6.31*	0.00	0.79	0.21	4.14*	0.00	2.70*	0.00
CD	0.05	0.47	0.65	0.25	-1.03	0.15	1.83**	0.03
CD_{LMadj}	6.78*	0.00	5.58*	0.00	4.42*	0.00	3.38*	0.00

Notes: * and ** denote the significance for at 0.01 and 0.05 levels, respectively

In our study, T (=24) > N (=11), and that means we need to focus on other tests except CD test because CD test is more efficient when N>T. When we check the table 2 and table 3, we can say that the null hypothesis of no cross-sectional dependence for total employment (TEM), total unemployment (TUN), youth employment (YEM), youth unemployment (YUN), and technological development (TEC), are rejected based on CD_{LM1}, CD_{LM2} and CD_{LMadj} test statistics. These findings show that a shock to these variables in CEE countries may also affect other countries.

After these cross-sectional dependence test results, we also need to do the slope heterogeneity (homogeneity) test before starting Kònya bootstrap panel Granger causality test. As we stated previously, the slope coefficients must be heterogeneous and therefore it must be tested whether they are heterogeneous or not.

If T>N in a study, the slope homogeneity statistic proposed by Swamy (1970) is often used to fulfil this requirement. Pesaran and Yamagata (2008) also presented a different standard version of the Swamy test that facilitates its applicability to larger panels. Denoted as $\tilde{\Delta}$, the first stage is to calculate the modified Swamy ($\tilde{S}$) statistic as illustrated in the equation (9) (Pesaran and Yamagata, 2008):

$$\tilde{S} = \sum_{i=1}^{N} \left(\hat{\beta}_i - \hat{\beta}_{WFE}\right)' \frac{x_i' M_\tau x_i}{\tilde{\sigma}_i^2} \left(\hat{\beta}_i - \hat{\beta}_{WFE}\right) \tag{9}$$

In this equation (9), $\hat{\beta}_i$ means that the pooled ordinary least squares estimator; $\hat{\beta}_{WFE}$, ise weighted and fixed effect pooled estimator; M_τ, means that identity matrix; and lastly $\tilde{\sigma}_i^2$ shows the estimator of σ_i^2. In the next step, the standardized version of Swamy statistic with asymptotic normal distribution always generated as in the following equation (10) below (Pesaran and Yamagata, 2008):

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \tag{10}$$

On the condition of $\sqrt{N}/T \to \infty$, we may say that the null hypothesis shows that slope coefficients are homogeneous when $(N, T) \to \infty$ is tested against the alternative hypothesis shows that slope coefficients are heterogeneous. And in this case, it is possible to write these hypotheses as in the following equation (11):

$$H_0: \beta_i = \beta; for\ all\ i,$$
$$H_1: \beta_i = \beta_{j;} for\ i \neq j \quad (11)$$

Besides all this, we can also give information about another test proposed by Pesaran and Yamagata (2008). This bias adjusted $\tilde{\Delta}_{adj}$ test which is applicable for smaller samples and whose error terms are distributed normally. It is as shown in the equation (12) below:

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{it})}{\sqrt{var(\tilde{z}_{it})}}\right) \quad (12)$$

After these explanations about test statistics, we can see the slope heterogeneity test results. In line with this theoretical information given, slope heterogeneity was tested and the results are as in the table 5.

Table 5: Slope Heterogeneity Test Results

	Model 1		**Model 2**		**Model 3**		**Model 4**	
	Stats.	Prob.	Stats.	Prob.	Stats.	Prob.	Stats.	Prob.
$\tilde{\Delta}$	3.46*	0.00	-0.59	0.72	2.26**	0.02	1.93**	0.02
$\tilde{\Delta}_{\mathbf{adj}}$	3.69*	0.00	-0.63	0.73	2.41*	0.00	2.06**	0.01
*, ** and *** denote the significance for at 0.01, 0.05, 0.10 levels, respectively.								

The slope heterogeneity test results show us that the null hypothesis that assumes the homogeneity of slope coefficients is rejected at 1% significance level for the Model 1, Model 3, and Model 4. But the homogeneity of slope coefficients is not rejected at 1% significance level for the Model 2. According to these results, we may say that the causality between technological development and total employment, youth employment, youth unemployment may differ as of CEE countries. However, the same cannot be said for the causality relationship between technological development and total unemployment. Because the slope heterogeneity test result of Model 2, which focuses on the relationship between technological development and total unemployment, was not found to be heterogeneous. Therefore, after this stage, causality testing was performed only for Model 1 (EM-TEC), Model 3 (YEM-TEC), and Model 4 (YUN-TEC).

Kar, Nazlıoğlu and Ağır (2011) stated that with the completion of these cross-section dependence and slope heterogeneity tests, it can be said that the first stage of Kònya bootstrap panel Granger causality test is completed and the panel Granger causality relationship between the variables should be tested. At this point it is necessary to remember that Wald test statistics and bootstrap critical values will be calculated by means of SUR system estimation which is created by Zellner (1962). According to Kar, Nazlıoğlu and Ağır (2011) quoted from Kònya (2006), The Kònya bootstrap panel Granger causality method requires defining a system containing two sets of equations, and this system can be expressed as shown in the equation (13) and equation (14) based on SUR method below:

$$Y_{1,t} = \alpha_{1,1} + \sum_{\mathrm{i}=1}^{ly_1} \beta_{1,1,\mathrm{i}} Y_{1,t-\mathrm{i}} + \sum_{\mathrm{i}=1}^{lx_1} \delta_{1,1,\mathrm{i}} X_{k,1,t-\mathrm{i}} + \varepsilon_{1,1,t}$$

$$Y_{2,t} = \alpha_{1,2} + \sum_{\mathrm{i}=1}^{ly_1} \beta_{1,2,\mathrm{i}} Y_{2,t-\mathrm{i}} + \sum_{\mathrm{i}=1}^{lx_1} \delta_{1,2,\mathrm{i}} X_{k,2,t-\mathrm{i}} + \varepsilon_{1,2,t}$$

(13)

…

$$Y_{N,t} = \alpha_{1,\mathrm{N}} + \sum_{\mathrm{i}=1}^{ly_1} \beta_{1,\mathrm{N},\mathrm{i}} Y_{N,t-\mathrm{i}} + \sum_{\mathrm{i}=1}^{lx_1} \delta_{1,\mathrm{N},\mathrm{i}} X_{k,\mathrm{N},t-\mathrm{i}} + \varepsilon_{1,\mathrm{N},t}$$

And also,

$$X_{k,1,t} = \alpha_{2,1} + \sum_{\mathrm{i}=1}^{ly_2} \beta_{2,1,\mathrm{i}} Y_{1,t-\mathrm{i}} + \sum_{\mathrm{i}=1}^{lx_2} \delta_{2,1,\mathrm{i}} X_{k,1,t-\mathrm{i}} + \varepsilon_{2,1,t}$$

$$X_{k,2,t} = \alpha_{2,2} + \sum_{\mathrm{i}=1}^{ly_2} \beta_{2,2,\mathrm{i}} Y_{2,t-\mathrm{i}} + \sum_{\mathrm{i}=1}^{lx_2} \delta_{2,2,\mathrm{i}} X_{k,2,t-\mathrm{i}} + \varepsilon_{2,2,t}$$

(14)

…

$$X_{k,N,t} = \alpha_{2,\mathrm{N}} + \sum_{\mathrm{i}=1}^{ly_2} \beta_{2,\mathrm{N},\mathrm{i}} Y_{N,t-\mathrm{i}} + \sum_{\mathrm{i}=1}^{lx_2} \delta_{2,\mathrm{N},\mathrm{i}} X_{k,\mathrm{N},t-\mathrm{i}} + \varepsilon_{2,\mathrm{N},t}$$

In these equations, Y is total employment (TEM), also youth employment (YEM), youth unemployment (YUN) and X is technological development (TEC), t refers time period (2000, 2001, 2002, …. ,2023) and N shows the number of CEE countries (11), l is the lag length, and ε signs the disturbance. As a result of this test, four possible causal relationships will be obtained (Kar, Nazlıoğlu and Ağır, 2011:689 quoted from Kònya 2006:979);

- There is one-way Granger causality relationship from X (TEC) to Y (EM, YEM, YUN) if not all $\delta_{1,\mathrm{j},\mathrm{i}}s$ are zero, but all $\beta_{2,\mathrm{j},\mathrm{i}}s$ are zero.
- There is one-way Granger causality relationship from Y (EM, YEM, YUN) to X (TEC) if all $\delta_{1,\mathrm{j},\mathrm{i}}s$ are zero, but not all $\beta_{2,\mathrm{j},\mathrm{i}}s$ are zero

- There is two-way Granger causality relationship between X (TEC) and Y (EM, YEM, YUN) if neither $\delta_{1,j,i}s$ nor $\beta_{2,j,i}s$ are zero.
- There is no Granger causality relationship between X (TEC) and Y (EM, YEM, YUN) if all $\delta_{1,j,i}s$ and $\beta_{2,j,i}s$ are zero.

According to Kònya (2006), “there is no simple rule to decide on the maximum lag, though there are formal model specification criteria to rely on. Ideally, the lag structure is allowed to vary across countries, variables and equation systems”. In our causality analysis, the maximum lag length is as 2 set as and the appropriate lag lengths for the systems have been determined according to Akaike (AIC) and Schwarz (SIC) information criterion. After all these information, we analysed the causality relationship between the variables for the CEE countries and the Kònya bootstrap panel Granger causality test results are reported on the table 6, table 7, and table 8 below.

Table 6: The Bootstrap Panel Granger Causality Test Results (Model 1)

Country	$TEC \nrightarrow TEM$				$TEM \nrightarrow TEC$			
	Wald Statistics [EC]	Bootstrap Critical Values			**Wald Statistics [EC]**	Bootstrap Critical Values		
		1%	**5%**	**10%**		**1%**	**5%**	**10%**
Bulgaria	2.99	30.82	14.60	9.54	50.81* **[0.00]**	41.70	26.74	21.00
Croatia	2.18	68.41	37.06	25.70	14.92** **[0.01]**	18.42	10.53	7.69
Czechia	2.42	46.97	25.52	17.68	9.02	26.61	14.22	9.86
Estonia	4.29	66.52	37.63	26.87	24.92** **[0.02]**	32.10	18.76	13.75
Hungary	4.12	23.65	12.46	8.57	4.27	76.94	48.46	38.09
Latvia	0.42	29.31	14.66	9.62	47.59* **[0.00]**	35.18	21.32	16.28
Lithuania	2.57	36.46	18.46	11.97	13.55*** **[0.08]**	26.70	16.59	12.73
Poland	3.06	15.94	8.36	5.46	248.52* **[0.00]**	169.87	103.43	87.00
Romania	1.38	48.74	23.35	15.14	17.22	49.89	33.46	27.48
Slovakia	0.08	41.13	21.36	15.23	65.86* **[0.00]**	44.30	26.91	20.61
Slovenia	3.52	51.79	27.43	19.18	28.26** **[0.02]**	37.02	23.18	17.66

Notes: *, ** and *** denote the significance for at 0.01, 0.05, 0.10 levels, respectively […] = EC: Estimated coefficients. Critical values obtained from 10.000 replications.

Model 1 in table 5, as previously stated, expresses the panel Granger causality relationship between total employment and technological development. According to this causality test results for 11 CEE countries, a one-way causality relationship from total employment to technological development was obtained in Bulgaria, Croatia, Estonia, Latvia, Lithuania, Poland, Slovakia and Slovenia. This finding provides a clue about the role of total employment in modern technological developments in these countries. No causality relationship was observed between total employment and technological development in Czechia, Hungary and Romania.

Table 7: The Bootstrap Panel Granger Causality Test Results (Model 3)

Country	TEC ↛ YEM				YEM ↛ TEC			
	Wald Statistics [EC]	Bootstrap Critical Values			Wald Statistics [EC]	Bootstrap Critical Values		
		1%	5%	10%		1%	5%	10%
Bulgaria	4.00	65.97	43.52	34.18	23.57	54.38	31.64	24.70
Croatia	29.74* **[0.00]**	26.61	16.44	12.27	27.82* **[0.00]**	22.05	11.90	8.21
Czechia	17.65** **[0.02]**	23.25	13.00	9.53	19.02** **[0.03]**	30.44	17.03	12.90
Estonia	7.67*** **[0.09]**	19.50	10.59	7.40	13.28** **[0.04]**	23.83	11.99	8.53
Hungary	5.62	55.56	34.47	26.45	8.03	100.89	61.67	48.18
Latvia	0.58	36.71	22.37	17.35	13.36*** **[0.08]**	31.09	17.44	12.07
Lithuania	1.72	53.97	32.56	24.42	8.10	32.12	19.37	13.43
Poland	25.89	53.82	36.20	28.87	4.08	114.65	76.09	62.92
Romania	8.84	74.25	42.87	32.56	16.30	69.34	47.12	37.68
Slovakia	13.34** **[0.02]**	16.37	8.98	6.36	14.87** **[0.04]**	25.60	14.61	10.40
Slovenia	6.53	51.90	33.58	26.65	11.61	55.88	35.61	27.51
Notes: *, ** and *** denote the significance for at 0.01, 0.05, 0.10 levels, respectively […] = EC: Estimated coefficients. Critical values obtained from 10.000 replications.								

The findings of the panel Granger causality test between youth employment and technological development are presented in the table 7 above. According to these findings, there is a mutual (bidirectional) causality relationship between youth employment and technological development in Croatia, Czechia, Estonia and Slovakia. It is understood that the use of modern technology is an important factor for youth employment in these countries. However, while there is a one-way causality relationship from youth employment to technological development in Latvia, it is also understood that there is no causality relationship between youth employment and technological development in Bulgaria, Hungary, Lithuania, Poland, Romania and Slovenia.

Table 8: The Bootstrap Panel Granger Causality Test Results (Model 4)

Country	TEC ↛ YUN				YUN ↛ TEC			
	Wald Statistics [EC]	Bootstrap Critical Values			Wald Statistics [EC]	Bootstrap Critical Values		
		1%	5%	10%		1%	5%	10%
Bulgaria	13.74** **[0.06]**	26.85	15.28	10.95	13.77** **[0.03]**	23.76	12.03	8.21
Croatia	1.49	124.17	80.27	64.05	5.46.789	40.84	23.38	16.74
Czechia	6.01	27.30	15.18	10.59	11.45*** **[0.07]**	30.67	14.71	9.66
Estonia	5.84	20.58	10.07	6.68	6.78	20.84	10.92	7.23
Hungary	5.41	31.12	20.18	15.30	20.22*** **[0.08]**	38.41	24.45	18.98
Latvia	7.81	23.80	12.58	8.77	0.03	53.64	29.04	19.88
Lithuania	13.05** **[0.01]**	15.71	7.68	4.99	8.46	24.32	14.27	10.39
Poland	22.04** **[0.02]**	29.72	18.14	13.61	34.43* **[0.00]**	29.86	18.22	13.59
Romania	3.94	52.30	32.14	25.06	7.88	31.77	21.32	17.38

Slovakia	2.85	74.57	49.94	39.39	1.42	110.30	71.05	55.43
Slovenia	8.25** **[0.04]**	15.49	8.12	5.39	8.49*** **[0.05]**	18.28	9.02	6.16
Notes: ***, **, and * denote the significance for at 0.10, 0.05 and 0.01 levels, respectively. […] = EC: Estimated coefficients. Critical values obtained from 10.000 replications.								

As mentioned before, since the expected results were not obtained in the preliminary tests required for Model 2, which focuses on the relationship between total unemployment and technological development, the causality relationship between total unemployment and technological development could not be tested. However, the causality relationship between youth unemployment and technological development was examined with the help of the established Model 4 and the results are presented in the table 8. According to the results in the table 8, there is a bidirectional causality relationship between youth unemployment and technological development in Bulgaria, Poland and Slovenia. This finding should be considered important in terms of presenting that the role of technological developments in youth unemployment developments in these countries is evident. On the other hand, a one-way causality relationship from youth unemployment to technological development was obtained in Czechia and Hungary, and a one-way causality relationship from technological development to youth unemployment was obtained in Lithuania.

CONCLUSION

Previous research shows that the hypothesis about the threat of high technological unemployment as a result of the use of modern technologies has not been confirmed. It is true that the processes of displacement of labor and its replacement by technology are noticed, but at the same time mechanisms compensating for employment losses are emphasized. It is worth emphasizing, however, that the economic literature draws attention to the high probability of accelerating the rate of diffusion of new technologies in the future and the possibility of intensifying the processes of displacement of labor from production processes, which may result in increasing difficulties in managing the labor force, especially in countries not affected by negative demographic trends.

Quite clear consequences can be seen in connection with the impact of modern technologies on changes in the structure of labor demand. It has been confirmed in empirical research that modern technologies cause a shift in the demand for labour towards jobs requiring high skills, that they cause a decline in the relative demand for labour in the field of routine tasks, and that the role of jobs in which non-routine tasks are performed, especially of an analytical nature, is increasing. The findings of the empirical analysis conducted within the scope of this study are presented below.

Figure 4: The Results of Causality Tests

TEM →TEC	YEM→TEC	YEM ↔ TEC	YUN ↔TEC	YUN →TEC	TEC → YUN
• Bulgaria • Croatia • Estonia • Latvia • Lithuania • Poland • Slovakia • Slovenia	• Latvia	• Croatia • Czechia • Estonia • Slovakia	• Bulgaria • Poland • Slovenia	• Czechia • Hungary	• Lithuania

• As can be observed from the information in the figure 4, technological developments have a causal relationship with total employment, youth employment and youth unemployment in many CEE countries. If we examine the findings in a little more detail, a one-way causal relationship was obtained from total employment to technological developments in Bulgaria, Croatia, Estonia, Latvia, Lithuania, Poland, Slovakia, Slovenia, and from youth employment to technological developments in Latvia and also from youth unemployment to technological developments in the Czechia and Hungary. These findings are important in terms of indicating that the changes in employment and unemployment developments in the countries in question are related to modern technology. On the other hand, youth employment and technological developments in Croatia, Czechia, Estonia, Slovakia, and youth unemployment and technological developments in Bulgaria are in a bidirectional causal relationship with each other, and these findings show that modern technologies are an important factor especially for the labor markets where young people are present in these countries. In contrast to all these, the finding that technological developments are the cause of youth unemployment in Lithuania seems quite remarkable. Based on these findings, it was evaluated that it would be useful and necessary to take into account the effects of developments in modern technologies on both employment and unemployment in CEE countries and to determine employment policies within this framework.

The findings of the study obtained are similar to the findings of some previous studies in the literature. For example, studies conducted by Abbasabadi & Soleimani (2021), Han (2021), Saka (2021) Naz & Altay (2023) generally address the relationship between technological development and unemployment-employment, and it has been proven that these variables are related to each other. In this respect, it can be stated that the findings of our study provide a new contribution to the literature. On the other hand, it can be said that studies on artificial intelligence, which is a new dimension of technological development, also have an impact on the labor market. As stated in Guliyev's (2023) study, the increase in artificial intelligence technologies is an important factor in reducing unemployment. Based on this, especially in CEE countries, which have a variable structure of unemployment developments, improving technological advancements—particularly increasing studies in the field of artificial intelligence—can be considered a necessary policy to reduce unemployment. At the same time, active employment policies to be implemented in these countries should aim to minimize the negative effects of technology on the workforce.

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