Research Article

The Impact of Digitalization on Unemployment in Türkiye: Investigating the Interactive Role of Education

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Abstract: Digitalization has been a key part of production, improving efficiency but also raising concerns about its impact on jobs. There is no consensus in the literature on the impact of digitalization on unemployment. Some believe it will replace workers, while others argue that it can boost productivity and create new job opportunities. To enrich this discussion from a different perspective, this study aims to explore how digitalization affects the unemployment rate and the role of education in this relationship during the period 2001–2023, using the Fully Modified Ordinary Least Squares (FMOLS) technique in Türkiye. To represent digitalization, the Principal Component Analysis (PCA) technique is applied to obtain a single indicator using the variables commonly used as proxies for digitalization in the literature, namely internet usage, broadband subscription, and mobile subscription. The results of this study can be listed as follows: i) Digitalization is associated with a higher unemployment rate. ii) However, when digitalization is coupled with an increase in the level of education, its effect on employment becomes more positive, as a more educated workforce is better equipped to adapt to the demands of the digital economy, ultimately reducing unemployment. iii) A higher GDP also decreases the unemployment rate. iv) To test the robustness of the FMOLS results, Canonical Cointegrating Regression (CCR) is also applied, confirming their reliability. Based on these findings, several policy implications are discussed, and recommendations for future research in this field are provided.

Keywords: Digitalization, Unemployment, Education
Jel Codes: C22, E24, I21

Dijitalleşmenin Türkiye'de İşsizliğe Etkisi: Eğitimin Etkileşimli Rolünün Araştırılması

Öz: Dijitalleşme üretimin önemli bir parçası haline gelerek verimliliği arttırmakta, ancak istihdam üzerindeki etkileri konusunda ise bazı endişelere sebep olmaktadır. Dijitalleşmenin işsizlik üzerindeki etkisi hakkında literatürde fikir birliği bulunmamaktır. Bazı çalışmalar dijitalleşmenin iş gücünün yerini alacağını öne sürerken, bazıları ise verimliliği artırarak yeni iş fırsatları yaratabileceğini savunmaktadır. Bu tartışmayı farklı bir bakış açısıyla zenginleştirmek amacıyla, mevcut çalışma dijitalleşmenin işsizlik oranını nasıl etkilediğini ve bu ilişkide eğitimin rolünü 2001–2023 döneminde Türkiye için, Tam Modifiye Edilmiş En Küçük Kareler (FMOLS) tekniğini kullanarak incelemeyi hedeflemiştir. Dijitalleşmeyi temsil etmek için, literatürde dijitalleşme için yaygın olarak kullanılan değişkenlerden, yani internet kullanımı, geniş bant aboneliği ve mobil abonelik değişkenlerinden tek bir gösterge elde etmek amacıyla Temel Bileşenler Analizi (PCA) tekniği uygulanmıştır. Çalışmanın sonuçları şu şekilde sıralanabilir: i) Dijitalleşme, daha yüksek bir işsizlik oranıyla ilişkilidir. ii) Fakat dijitalleşmeyle beraber eğitim seviyesinde artış meydana geldiğinde dijitalleşmenin istihdam üzerindeki etkisi pozitife dönmektedir, yani işsizlik oranını azalmaktadır. Çünkü daha eğitimli bir iş gücü dijital ekonominin işçi taleplerine cevap vererek işsizliğin azalmasına neden olmaktadır. iii) Daha yüksek bir GSYİH'de işsizlik oranını düşürmektedir. iv) FMOLS ile elde edilen sonuçların güvenilirliğini test etmek için, Kanonik Eşbütünleşme Regresyonu (CCR) metodu da uygulanmış ve sonuçların güvenilirliği doğrulanmıştır. Bu bulgulara dayanarak, birkaç politika önerisi tartışılmış ve bu alanda gelecekte yapılması planlanan araştırmalar için önerilerde bulunulmuştur.

Anahtar Kelimeler: Dijitalleşme, İşsizlik, Eğitim
Jel Kodları: C22, E24, I21

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1. Introduction

Digitalization has recently attracted the attention of many researchers and scientists, becoming the subject of numerous studies due to its important role in human activities. Although various definitions of digitalization exist, the most widely accepted one in the literature is the process of converting information from an analog to a digital environment (Gobble, 2018, p. 56). Digitalization also involves the use of developing technologies across all fields (Balsmeier & Woerter, 2019, p. 1). Digitalization improves living standards by offering convenience in various fields, from healthcare to education. For example, the use of digital tools like blood pressure monitors and electronic health records enables faster healthcare delivery to more people. Also, online education platforms reach a wider audience, and digital visuals enhance understanding and the quality of education. Besides, digitalization also facilitates easier communication, particularly in trade, helping to expand markets quickly. Moreover, it eliminates the hassle of physical communication, allowing to save time and transportation cost, thereby reducing overall expenses. Additionally, digitalization promotes a paperless environment (Gobble, 2022, p. 56), reducing waste and minimizing its environmental destruction impact.

However, the integration of digitalization into production processes, such as business operations and industries, has sparked concerns about its potential to replace the workforce. In fact, Aly (2022, p. 241) highlights that this debate dates back to Aristotle's time, and the concept of technological unemployment gained popularity with Keynes in the 1930s. Contrary to this point, Schumpeter (1976), with his creative destruction approach, explained that each innovation would destroy the existing order but would replace it with a more effective and efficient system. In contrast to the concept of technological unemployment, he argued that each innovation creates its own job field, thus generating new employment opportunities.

With the increasing role of technology in production, digitalization has not only enhanced efficiency but also highlighted the importance of innovation for competitiveness. Each new technological advancement creates a demand for workers in that field, supporting the idea that digitalization, within the framework of creative destruction, can boost employment and reduce unemployment (Vivarelli, 2014, p. 125). However, the impact of digitalization on employment is twofold: while it generates new job opportunities, it also replaces human labor in certain areas, particularly for low-skilled workers who are increasingly substituted by more efficient and faster automation. On the other hand, in roles requiring uniquely human attributes such as creativity, problem-solving, and social intelligence, digitalization serves as a complement rather than a substitute. According to study of Lassébie & Quintini (2022, p. 10), 28% of workers in OECD countries are at risk of job loss due to automation. Nevertheless, only 5% of jobs involve highly human-dependent bottleneck tasks, making their complete replacement by technology unlikely.

The main motivation for this study is that the relationship between digitalization and employment has existed for a long time, yet there is still no clear conclusion about it in the literature. Within this framework, this research aims to analyze the impact of digitalization on Türkiye's unemployment rate and examine the role of education in this relationship. This study selects three variables, commonly used in the literature and available for Türkiye, as proxies for digitalization, namely the percentage of internet users, mobile subscription rate, and broadband subscription rate (see Akalın, 2024). Further details on these variables are provided in the data section. The trends of these three variables from 2001 to 2023 are presented in Figure 1. The data show a consistent increase in all three variables since 2001, except for a slight decline in internet usage in 2009. Aside from this, all variables follow a similar pattern. One notable point in the figure is that broadband subscription was close to 0% in 2001. However, after 2004, it grew rapidly, reaching approximately 23% by 2023.

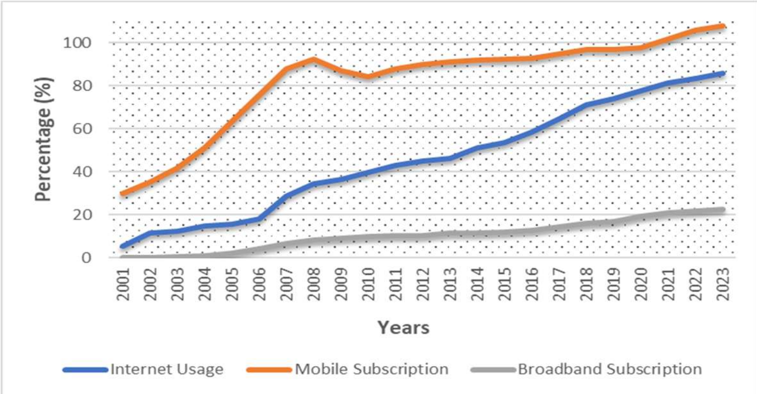

Figure 1. Changes in Digitalization Indicators (Source: World Bank Indicator)

Although digitalization has facilitated human life and improved quality of life, its impact on employment remains one of today's ongoing discussions. Research on this topic is still quite limited, and this study differs from existing studies in the following ways: First, to the best of my knowledge, it is the only study that examines the impact of digitalization on employment in Türkiye. More importantly, by investigating the role of education in this relationship, it offers an innovative perspective. The study also addresses serial correlation and endogeneity problems, using the FMOLS method to ensure more accurate and reliable results. Furthermore, a robustness check is conducted, applying an alternative method of the CCR to enhance the reliability of the findings. Based on these reliable results, the study presents policy implications. These aspects demonstrate the significant contributions of this study to the literature.

The structure of this study is organized as follows: In the Literature Review section, previous studies on this topic are briefly summarized, and the limited number of studies in this area is highlighted. The data and methodology section explains in detail how the data representing digitalization was obtained and describes the other variables included in the model. Additionally, justifications for the chosen methodology are provided. The next section presents the results of the analysis, and the findings are discussed. In the robustness check section, an alternative method is applied to test the reliability of the findings. Finally, in the conclusion section, the main findings are summarized, and policy implications and recommendations for future research in this field are provided.

2. Literature Review

Although the impact of digitalization on unemployment has been the subject of some studies, there is no consensus on this issue, and the results remain mixed. This topic is still actively debated. The number of discussions addressing this topic in the literature is very limited, and most of them are summarized in Table 1. As seen, some studies conclude that digitalization will increase unemployment (see Acemoglu & Restrepo, 2017; Balsmeier & Woerter, 2019), while others suggest that it will reduce unemployment by increasing employment (see Arntz et al., 2016; Sinha et al., 2023). Even some have revealed that while digitalization reduces job opportunities for certain groups, it increases job demand and eases job-finding opportunities for others (Michaels et al., 2014; Arısoy, 2024). Additionally, several studies find no significant relationship between digitalization and unemployment at all (Koç & İzhi-Şahpaz, 2023; Ünlüoğlu & Aydınbaş, 2023). The lack of agreement in the literature might be due to several reasons: different studies focus on countries or groups of countries at various levels of development, use different econometric approaches, and concentrate on different time periods.

One study that addresses the impact of digitalization on unemployment in a different way is conducted by Acemoglu & Restrepo (2017). They divide unemployment into skilled, medium-skilled, and unskilled unemployment categories and offer a new perspective to explain the disagreement in the literature. They found that digitalization creates new job opportunities for skilled workers, increasing demand for this group and thus reducing unemployment. On the other hand, digitalization replaces unskilled and medium skilled workers by performing the same tasks more efficiently, consequently increasing unemployment for this group. They found no significant effect for medium-skilled workers. Similar findings are also found by Balsmeier & Woerter (2019). However, their overall conclusion was that digitalization reduces unemployment.

Michaels et al (2014) similarly examined the impact of digitalization on employment in 11 developed countries. The study found that with digitalization, the demand for medium-skilled workers decreased, while the demand for higher-skilled workers increased. As a result, the findings support the job polarization hypothesis, which refers to the shrinking demand for middle-skilled jobs while employment opportunities grow at both the high-skill and low-skill ends of the labor market. From another perspective, Hazarika (2020) assesses the impact of digitalization on employment in the Indian banking sector. He concludes that due to digitalization, fewer clerks and sub-staff are employed, highlighting its negative effect on employment.

Other studies conducted on this topic are summarized in Table. A key difference in this study compared to others is the inclusion of education level in the analysis of the relationship between digitalization and unemployment. In other words, this study examines how changes in education level affect the impact of digitalization on unemployment. The main motivation for focusing on education can be explained as follows: Having a workforce that internalizes digitalization along with education enables more efficient production, allowing workers to adapt to technological advancements and find opportunities in newly created job fields resulting from digitalization. This approach provides a fresh perspective, making a significant contribution to the literature. Additionally, as seen in Table 1, the impact of digitalization on unemployment has generally been analyzed at the firm or industry level and mostly qualitative methods are employed in these studies. Only few studies have used panel data and quantitative methods for this analysis. To the best of my knowledge, this study is the first and only one that examines the impact of digitalization on unemployment using the FMOLS and CCR methods for the case of Türkiye. Within this framework, this study also makes a valuable contribution by shedding light on this relationship.

Table 1. Review of Relevant Studies

Authors	**Sample Country(ies) /Period**	**Technique**	**Variables as proxies for digitalization**	**Results**	
				Higher unemployment	**Lower unemployment**
Arısoy (2024)	20 Workers	Phenomenological research	Technological tools	Supported	Supported
Sinha et al. (2023)	70 Developing countries, 2001-2019	GMM	International internet bandwidth		Supported
Aly (2022)	25 Developing countries, 2017	OLS, GLS, FGLS	Digital transformation index		Supported
Cirillo et al. (2021)	500 Professional group in Italy, 2011-2016	WLS	Digital use index, Digital task index		Supported
Kogan et al. (2021)	Industries in the USA, 1850-2010	Survey	Technological innovation	Supported	
Hazarika (2020)	Indian Banking sectors, 2005-2015	OLS	Operational profitability	Supported	
Balsmeier & Woerter (2019)	5700 Firms, 2014-2015	OLS, IV	Investment in Digitalization	Supported	Supported
Arntz et al. (2016)	OECD, 2012	Imputation approach	2-digit ISCO		Supported
Harrison et al. (2014)	4 Developed Countries, 1998-2000	OLS, IV	Innovation		Supported
Michaels et al. (2014)	11 Developed countries, 1980-2004	FE, IV	Information and communication technologies	Supported	Supported

3. Data and Methodology

This study examines the impact of digitalization on the unemployment rate in Türkiye from 2001 to 2023 using the Fully Modified Ordinary Least Squares (FMOLS) method. To conduct the analysis, three separate regressions are performed with different control variables. The analyses are mainly presented as equations below:

$$lnUNEMP_t = \alpha + \beta_1 \mathrm{DIGI}_t + \beta_2 \mathrm{X}_t + \varepsilon_t \tag{1}$$

where lnUNEMP represents the unemployment level and is included in the model as the dependent variable. The subscript t denotes the years. DIGI is the independent variable representing digitalization, while X refers to the control variables, lnGDP, lnMNWG, lnEDU, and lnINF, used in the models. Detailed information on these variables, including their definitions, sources, and metrics, is provided in Table 2.

Table 2. Dataset Description

Symbol	Definition	Metric	Data Source
lnUNEMP	Unemployment Rate	Log-transformed value	World Bank
DIGI	Digitalization	Unit	World Bank
lnGDP	Real GDP (2015 $)	Log-transformed value	World Bank
lnMNWG	Mini Wage	Log-transformed value	TUIK
lnEDU	Number of University Graduates	Log-transformed value	MEB
lnINF	Inflation (CPI)	Log-transformed value	World Bank

To measure digitalization in the literature, various indicators are used, including the Digital Adoption Index (DAI), the Digital Economy and Society Index (DESI), mobile subscriptions (MS), internet usage (IU), and broadband subscriptions (BS) (see Başol et al., 2023; Sinha et al., 2023; Akalin, 2024). Among these, DAI data is only available for the years 2014 and 2016, while DESI data is available only for European Union member countries. However, common data for MS, IU, and BS is available starting from 2001 for Türkiye, so this study covers the period from 2001 to 2023.

Before using these three variables in regression analysis, a correlation matrix was created to check for potential high correlations between them. As shown in Table 3, the correlation between MS and IU is 94%, between MS and BS is 93%, and between IU and BS is 99%.

Table 3. Correlation Matrix for MS, IU, and BS

Variables	MS	IU	BS
MS	1.0000		
IU	0.9417	1.0000	
BS	0.9299	0.9909	1.0000

Since these indicators are highly correlated, using them together could lead to multicollinearity issues. Additionally, they exhibit similar patterns, meaning they essentially represent the same concept. Therefore, instead of using all three variables separately, Principal Component Analysis (PCA) was applied to combine them into a single variable. This new variable will be used as a representative measure of digitalization.

The results of the PCA analysis are presented in Table 4. As shown, the first component accounts for nearly 97% of the total variance, indicating that most of the information in the dataset is captured by this component. Therefore, it is preferable to use the first component as a proxy for digitalization in this study.

Table 4. PCA Results for the Three Digitalization Variables

Component	Eigenvalue	Differences	Proportion	Cumulative
Comp 1	2.90852	2.8251	0.9695	0.9695
Comp 2	0.0830	0.7455	0.0277	0.9972
Comp 3	0.0085		0.0028	1.0000

The statistical information on the data used in the analysis is summarized in Table 5. The digitalization variable has the lowest mean value, close to zero. It is not used in its natural logarithm form due to the presence of negative values. However, it has the highest standard deviation, indicating significant variation in digitalization over the years. lnUNEMP has a lower mean value and also the lowest standard deviation, at 0.12, reflecting stability in the unemployment rate. Similarly, lnINF has a low mean value of 2.60; however, unlike lnUNEMP, its standard deviation is almost six times higher, indicating significant fluctuations in the inflation rate from year to year. As expected, lnGDP has the highest mean value, at 27.29. However, its standard deviation is relatively low, at 0.35, suggesting that GDP in Türkiye has remained relatively stable over the years. The other variables can be interpreted in a similar manner.

Table 5. Summary Statistics

Variable	Obser.	Mean v.	Stand. Dev.	Min.	Max.
lnUNEMP	23	2.3727	0.1229	2.1259	2.6409
DIGI	23	-8.58e-09	1.7054	-2.9082	2.7173
lnGDP	23	27.2989	0.3493	26.6895	27.8585
lnMNWG	23	7.1229	1.0668	5.4027	9.7237
lnEDU	23	13.0208	0.7636	11.2299	14.3339
lnINF	23	2.6042	0.7405	1.8327	14.3339

This study employs the FMOLS method, developed by Phillips & Hansen (1990), for long-run analysis. Using the FMOLS method offers several advantages: First, it addresses the endogeneity problem that may arise in this model, yielding consistent and reliable results (Ying et al., 2014, p. 31). In addition, FMOLS helps overcome the issue of serial correlation in the error term (Anoruo & Braha, 2005, p. 45). Moreover, FMOLS performs better in small samples compared to other long-run estimators (Pegkas, 2015, p. 129). However, this method is applicable only when the variables are cointegrated of order one. Due to these advantages, the FMOLS method is chosen for this study.

The FMOLS method adjusts the coefficients obtained from the OLS technique to address endogeneity and serial correlation, as shown in the equation below.

$$\tilde{\beta}_{\mathrm{FMOLS}} = \left[\sum_{t-1}^{T}(Xt - \bar{X})(Xt - \overline{X})'\right]^{-1}\left[\sum_{t-1}^{T}(Xt - \bar{X})(Y_t^{*} - \overline{Y^{*}})\right] \quad (2)$$

where $\bar{X}$ and $\overline{Y^{*}}$ refer to the sample means of Xt and Y_t^{*}.

4. Empirical Results

Initially, some pretests should be conducted to ensure that the FMOLS method can be applied and that the results are consistent.

4.1. Pre-Estimation Tests

First, before proceeding with the analysis, the correlation between the variables was examined, and the results are presented in Table 6. Since the correlation coefficient between the independent variables does not exceed 80%, there is no concern about multicollinearity.

Table 6. Pairwise Correlations

Variables	lnUNEMP	DIGI	lnGDP	lnMNWG	lnEDU	lnINF
lnUNEMP	1.0000					
DIGI	0.8217	1.0000				
lnGDP	-0.3700	-0.0860	1.0000			
lnMNWG	0.7720	0.7679	0.1590	1.0000		
lnEDU	0.3270	0.1204	-0.1666	0.4295	1.0000	
lnINF	0.6727	0.6580	0.0205	0.7524	0.4359	1.0000

One of the essential tests is to check the stationarity of the variables. To achieve this, the Augmented Dickey-Fuller (ADF) unit root test, developed by Dickey & Fuller (1979), is employed, and the findings are presented in Table 7. As demonstrated, all variables are non-stationary at the level but become stationary, I(1), after taking their first differences. To verify the robustness of the stationarity level, another unit root test, the Phillips-Perron (PP) Unit Root Test, introduced by Phillips and Perron (1988), is applied. The results confirm the findings that all variables are cointegrated at order one, I(1).

Table 7. Unit Root Test (ADF and PP)

	ADF Unit Root Test		PP Unit Root Test	
Variable	**Level**	**First Difference**	**Level**	**First Difference**
lnUNEMP	-2.9656	-3.8251**	-2.0947	-3.8201**
DIGI	-2.7198	-3.2619**	-1.7879	-3.7164**
lnGDP	-2.4933	-3.6515**	-2.5834	-3.6785**
lnMNWG	-2.4638	-3.8584**	-1.5731	-3.8972**
lnEDU	-1.7732	-3.3638**	-2.1365	-4.3049***
lnINF	-1.0942	-5.1709***	-1.6944	-5.3835***

The final essential pretest is to check whether there is cointegration between the variables, as it indicates the long-run relationship. Since FMOLS provides long-run results, the presence of cointegration is a prerequisite assumption. To analyze this, the Johansen cointegration test developed by Johansen (1991) is applied, as all the variables are I(1), making this test appropriate. First, cointegration is tested for Model 1, and the results are presented in Table 8. Both the trace and maximum eigenvalue statistics are reported separately. Their null hypotheses state that there is no cointegration among the variables, which can be rejected if the test statistics exceed the critical values. In both tests, the hypothesis of r=0, which claims that there is no cointegration, is rejected at the 5% significance level. Therefore, this suggests that at least one cointegrating relationship exists in Model 1.

Table 8. The Results of Cointegration Test for Model 1

Trace Statistics				
No. of CE(s)	**Eigenvalue**	**Trace Stat.**	**Critic. Value**	**Prob.**
r = 0***	0.9131	93.6319	69.8189	0.0002
r ≤ 1*	0.7307	47.2141	47.8561	0.0574
r ≤ 2	0.5403	22.2863	29.7971	0.2829
r ≤ 3	0.2858	7.5210	15.4947	0.5179
r ≤ 4	0.0575	1.1255	3.8414	0.2887
Max. Eigenvalue Statistics				
No. of CE(s)	**Eigenvalue**	**Max. Eigen Stat.**	**Critic. Value**	**Prob.**
r = 0***	0.9131	46.4178	33.8768	0.0010
r ≤ 1	0.7307	24.9278	27.5843	0.1054
r ≤ 2	0.5402	14.7653	21.1316	0.3057
r ≤ 3	0.2858	6.3955	14.264	0.5630
r ≤ 4	0.0575	1.1255	3.8414	0.2887

Similarly, the Johansen cointegration test was applied for Model 2, and the results are presented in Table 9. As seen, in the trace statistics, the probability value of r≤2 is less than 0.05, leading to the rejection of the null hypothesis, which indicates the presence of a third cointegration relationship. The max. eigenvalue statistics show that the p-value of r≤1 is lower than 0.05, but the p-value of r≤2 is not, suggesting the presence of only two cointegration relationships. Consequently, both statistics confirm the presence of cointegration in Model 2.

Table 9. The Results of Cointegration Test for Model 2

Trace Statistics				
No. of CE(s)	**Eigenvalue**	**Trace Stat.**	**Critic. value**	**Prob.**
r = 0**	0.9184	107.2393	69.8189	0.0000
r ≤ 1**	0.7856	59.6134	47.8561	0.0027
r ≤ 2**	0.6018	30.3554	29.7971	0.0431
r ≤ 3	0.3828	12.8598	15.4947	0.1200
r ≤ 4	0.1765	3.6898	3.8414	0.0547
Max. Eigenvalue Statistics				
No. of CE(s)	**Eigenvalue**	**Max. Eigen Stat.**	**Critic. Value**	**Prob.**
r = 0**	0.9185	47.6259	33.8768	0.0007
r ≤ 1**	0.7855	29.2579	27.5843	0.0302
r ≤ 2	0.6018	17.4956	21.1316	0.1499
r ≤ 3	0.3828	9.1700	14.2646	0.2723
r ≤ 4	0.1765	3.6898	3.8414	0.0547

The cointegration test is also applied to Model 3, and the results can be seen in Table 10. The trace statistics indicate the presence of a fifth cointegration relationship due to the rejection of the null hypothesis for r≤4. The Max. The eigenvalue statistics also support the existence of five cointegration relationships. As a result, it is clear that there is a long-term relationship among the variables in Model 3 according to both statistics.

Table 10. The Results of Cointegration Test for Model 3

Trace Statistics				
No. of CE(s)	**Eigenvalue**	**Trace Stat.**	**Critic. Value**	**Prob.**
r = 0**	0.9989	260.8442	95.7536	0.0000
r ≤ 1**	0.9603	129.9188	69.8188	0.0000
r ≤ 2**	0.8129	68.6151	47.8561	0.0002
r ≤ 3**	0.6624	36.7658	29.7970	0.0067
r ≤ 4**	0.5673	16.1317	15.4947	0.0401
r ≤ 5	0.0111	0.2129	3.8414	0.6445
Max. Eigenvalue Statistics				
No. of CE(s)	**Eigenvalue**	**Max. Eigen Stat.**	**Critic. Value**	**Prob.**
r = 0**	0.9989	130.9254	40.0775	0.0000
r ≤ 1**	0.9603	61.3036	33.8768	0.0000
r ≤ 2**	0.8129	31.8493	27.5843	0.0133
r ≤ 3**	0.6624	20.6341	21.1316	0.0586
r ≤ 4**	0.5673	15.9188	14.2646	0.0271
r ≤ 5	0.0111	0.2129	3.8414	0.6445

4.2. Empirical Analysis of FMOLS Results and Discussion

To assess the impact of digitalization on the unemployment level in Türkiye, three models are established, and their results are presented in Table 11. In Model 1, the coefficient of DIGI enters the regression positively and is statistically significant, indicating that the unemployment rate increases with higher digitalization. More specifically, a 1% increase in DIGI is associated with a 1.8% increase in the unemployment rate. The finding of an increasing effect of DIGI on unemployment aligns with the studies of Hazarika (2020), Kogan et al. (2021). GDP is also included as a control variable, and as expected, it shows that higher GDP is linked to a lower unemployment rate. This is because economic growth allows for the employment of more machines and workers, creating an inverse relationship between GDP and the unemployment rate. This finding is supported by the studies of Maitah et al. (2015), Sitompul & Simangunsong (2019). The application of a minimum wage policy is also considered a determinant of the unemployment level, so it is incorporated into the model. As expected, an increase in lnMNWG is associated with a higher unemployment rate due to the increased cost of hiring workers. This result is consistent with the studies of Majchrowska & Zólkiewski

(2012), Paun et al. (2021). Finally, the number of university graduates is included in the model as a representation of education. The coefficient of InEDU is negative and statistically significant, indicating that as the education level in the country increases, the unemployment rate decreases. This result is in line with the findings of Malik (2010), Riddel & Song (2011).

To analyze the role of education in the relationship between digitalization and unemployment rate, an interaction term is created by multiplying digitalization with education, and this term is represented by DIGIEDU. The reason for the multiplication is to represent the combined effect of both digitalization and education. This is a commonly used mathematical approach in the literature, as it enables researchers to capture the role of education in the effect of digitalization on unemployment. This interaction term is included in Model 2, but to avoid multicollinearity issues, the education variable is excluded from the model. Model 2 also serves to check the robustness of the findings obtained in Model 1. The coefficient of DIGI remains positive and significant, demonstrating that a higher level of digitalization leads to a higher unemployment rate, confirming the previous finding. The control variables also show a similar pattern to those in Model 1. The coefficient of DIGIEDU is negative and significant, indicating that as education levels increase, the negative impact of digitalization on unemployment weakens. In other words, higher education levels help individuals adapt to digitalization, which reduces the unemployment rate.

In addition to the variables employed in Model 2, the lnINF variable is incorporated as a control variable, and the findings are provided under Model 3. As shown, DIGI and the other control variables remain the same in their effect on the unemployment rate, demonstrating the robustness of the findings. The sign of lnINF is negative, indicating that a higher inflation rate results in a lower unemployment rate, but it is not statistically significant.

Table 11. Results of Long-Run Relationship Estimation via FMOLS

Variables	Model 1	Model 2	Model 3
DIGI	0.01862*** (0.000)	0.06783*** (0.0000)	0.05965*** (0.0004)
lnGDP	-1.8739 *** (0.0000)	-2.1241*** (0.0000)	-2.0967*** (0.0000)
lnMNGW	0.4536*** (0.0000)	0.6108*** (0.0000)	0.5985*** (0.0000)
lnEDU	-0.2540** (0.0502)		
DIGIEDU		-0.4030*** (0.0003)	-0.3409*** (0.0039)
lnINF			-0.1631 (0.3357)
Cons.	49.3940*** (0.0000)	54.8036*** (0.0000)	54.1795*** (0.0000)
Adj. R-Squared	0.5772	0.5973	0.5681

With the integration of technological tools into production through digitalization, the demand for labor in traditional, physically demanding jobs has significantly decreased (Ovretveit, 2020, p. 334). Additionally, another factor contributing to unemployment is that traditional workers often lack the necessary skills to adapt to emerging technologies. Within this context, this study's finding that digitalization increases unemployment is supported by these factors. However, Schumpeter (1976, p. 82-83), who introduced the concept of creative destruction, argued that every new technology creates new employment opportunities, suggesting that its impact on unemployment is not necessarily negative. Furthermore, digitalization within existing industries allows workers to continue their employment by adapting to technological advancements. Given that keeping up with digitalization is largely dependent on education, it is evident that a more skilled workforce will be in higher demand. In this regard, the increase in educated labor can counteract the unemployment-inducing effects of digitalization, which explains the rationale behind the finding of this study, concluding that the availability of higher-educated employees helps reduce the unemployment-increasing effect of digitalization.

The reducing effect of GDP on unemployment is explained by the argument that increased production is possible through the use of more production factors. In other words, higher production growth can be achieved through an increase in labor, which is one of the key determinants of production. In this context, an increase in GDP raises labor demand, which in turn increases employment and reduces unemployment.

As previously mentioned, the minimum wage policy sets the lowest amount an employer is required to pay workers. Since wages represent income for workers but a cost for employers, an increase in the minimum wage simultaneously increases costs for employers, reducing their profits. Employers, aiming to maximize their profits, respond to rising costs by employing fewer workers, often leading to layoffs. This explains the increasing effect of minimum wages on unemployment.

With rising education levels, more qualified individuals enter the labor market, enabling them to work in technologically advanced production facilities, as required by modern times. In this regard, education enhances workers' skills, making it easier for them to find jobs, thereby increasing employment levels and contributing to the reduction of unemployment. Within this discussion framework, the impact of education on reducing unemployment can be explained through these arguments.

4.3. Robustness Check

As an additional robustness check, the Canonical Cointegration Regression (CCR) method developed by Park (1992) is applied to assess the stability of the results obtained using the FMOLS technique. This method can also overcome issues of endogeneity and serial correlation, similar to the FMOLS. However, the reason for choosing the CCR is that it can handle multiple cointegrating relationships and address potential multivariate complexities, which underscores the main reason for selecting this method for the robustness check (Park, 1992, p. 120). Using the CCR method, the impact of digitalization on unemployment is also analyzed based on three models, and the results are presented in Table 12. In all models, the coefficient of DIGI is positive, and the magnitude is similar to the coefficient obtained using FMOLS, showing that the increasing effect of digitalization on the unemployment rate is reliable and robust. The DIGIEDU variable in Models 2 and 3 also show a similar pattern, with a negative and significant coefficient, confirming that the effect of digitalization on reducing unemployment becomes more pronounced as education levels rise, further supporting the robustness of the findings estimated by the FMOLS. The other control variables also provide results that support the findings from the previous FMOLS analysis.

Table 12. Results of Long-Run Relationship Estimation via CCR

Variables	Model 1	Model 2	Model 3
DIGI	0.01944*** (0.0001)	0.06911*** (0.0001)	0.0611** (0.0101)
lnGDP	-1.8577*** (0.0000)	-0.2119*** (0.0000)	-0.2097*** (0.0000)
lnMINW	0.4319*** (0.0000)	0.6023*** (0.0000)	0.5921*** (0.0000)
lnEDU	-0.2745 (0.2155)		
DIGIEDU		-0.4103*** (0.0014)	-0.3496** (0.0454)
lnINF			-0.1872 (0.3971)
Cons.	49.1222*** (0.0000)	54.7243*** (0.0000)	54.2512*** (0.000)
Adj. R-Squared	0.5609	0.5934	0.5629

5. Conclusion

With digitalization, technological devices have started to play a significant role in every aspect of human life. As a result, the impact of digitalization on various socio-economic indicators has become a subject of research. One of the most significant areas where technological advancements are applied is undoubtedly the field of production. Therefore, digitalization and economic activities are closely interconnected. Within this framework, this research aims to analyze the impact of digitalization on the unemployment rate in Türkiye over the period 2001–2023 using the FMOLS technique. Furthermore, the role of education in the relationship between digitalization and the unemployment rate is also examined. The findings of the study indicate that increased digitalization exacerbates unemployment. However, when digitalization is accompanied by a rise in education levels, it has a positive effect on employment, thereby reducing unemployment. Increases in GDP and education also contribute to higher employment levels, leading to a reduction in unemployment. On the other hand, the implementation of a minimum wage serves as a cost factor for employers, decreasing employment levels and increasing the unemployment rate. It has been observed that inflation does not have a significant effect on the unemployment rate. Similar findings are obtained when the CCR method is applied, confirming the robustness of the results.

Based on the findings obtained, some policy implications can be outlined as follows: First, although digitalization on its own is seen as a factor that increases unemployment, when combined with an increase in the level of education, it creates a more skilled workforce, thereby reducing the unemployment rate. Within this context, placing greater emphasis on education and increasing the number of university graduates will better prepare individuals for digitalization and contribute to the development of a more qualified workforce. Moreover, it has been observed that education alone also reduces unemployment. Therefore, a higher level of education enhances employment through two channels, creating a win-win situation. While prioritizing education, necessary measures should also be taken to support digitalization, as it is both a necessity in today's world and a crucial factor in international competition. This can help achieve a significant reduction in unemployment. In addition, GDP is another key factor influencing unemployment, as higher GDP levels contribute to its reduction. Therefore, economic growth not only elevates a country to a higher economic status but also helps lower unemployment rates. Finally, minimum wage is also found to be a factor determining the unemployment level. Therefore, when setting the minimum wage, its impact on unemployment should be carefully analyzed and not overlooked.

This study is limited to examining the impact of digitalization on unemployment for the whole economy without distinguishing between different sectors. Future research may explore the effects of digitalization on unemployment in specific industries. This study conducts a time series analysis and focuses solely on a single country. Future studies could compare countries with similar levels of development and unemployment by analyzing them separately and assessing the role of education in this relationship. Additionally, a similar study could be conducted in a panel format for a group of countries.

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