International Journal of Social Science and Economic Research

ISSN: 2455-8834

Volume:09, Issue:08 "August 2024"

The Influence of Digitalization on The European Labour Market – An Advanced Econometric Approach

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DOI: 10.46609/IJSSER.2024.v09i08.001 URL: https://doi.org/10.46609/IJSSER.2024.v09i08.001

Received: 25 July 2024 / Accepted: 10 August 2024 / Published: 15 August 2024

ABSTRACT

Considering the significant impact that digitalization and digital transformation have on the economy and society, this paper aims to provide a comprehensive analysis of the effects of this phenomenon across European Union Member States. The analysis will be realized using the Gaussian Graphical Model, based on two sets of indicators: one representative of digital infrastructure and human capital, and the other of the socio-economic impact, for the time period 2011-2022. The findings presented in this paper will show the complex relationship between digitalization and the labour market, highlighting both positive and negative connections between the variables analyzed. Furthermore, the study will emphasize the growing importance of digital transformation in all its facets.

Keywords: Digitalization, Labour market, Gaussian Graphical Model, Economy, European Union

1. Introduction

The phenomenon called digitalization enjoys an increasing importance and interest with the passage of time. Whether we are talking about the business, economic or social environment, the impact of digital transformation has an upward trend, this being correlated with a better performance of enterprises in terms of productivity, management practices, operational strategies, innovation, economic growth and places better paid jobs, so digital transformation is seen as essential for EU businesses to gain competitive advantage (Suciu et al., 2019).

The main objective of this research is to present the interplay between digitalization and the labour market through the econometric analysis of several representative indicators, by applying the Gaussian Graphic Model.

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The structure of the paper comprises a brief literature review, presenting ideas about the connection between labour market and digital transformation nowadays, then a part of data and methodology, which presents the variables and the econometric models used in the study, obviously a part with results and discussion, followed by the final part with conclusions.

2. A brief literature review

Digitalization has fundamentally transformed the labour market in recent decades, influencing the way we work, interact and develop professionally. This rapid transition to a digital economy has brought both opportunities and challenges for employers and employees (Grima et al., 2023).

Codagnone et al. (2020, p 19) define digitalization as "a cultural, social, and economic transition in which digital technologies play a central role in shaping human behaviors and interactions". This definition underlines the broad impact of digitalization on society and culture. One of the most discussed topics related to digitalization is the automation of workplaces through robots and artificial intelligence. Studies show that a significant number of jobs are likely to be automated. For example, a report by the McKinsey Global Institute (2020) estimates that up to 375 million workers, globally, may have to change their occupation by 2030 due to automation. While automation eliminates some jobs, digitalization also creates new opportunities. New technologies require skilled workforce in areas such as programming, data analytics, cybersecurity, and digital project management (Cristea et al., 2023). According to the World Economic Forum (2020), it is estimated that by 2025, the digital economy will create 97 million new jobs. As digitalization has progressed, technologies such as artificial intelligence, robotics, and data analytics have become increasingly prevalent. They have transformed numerous industries, from manufacturing and logistics to healthcare and education. Today, digitalization is an integral part of our daily lives, influencing almost every aspect of society.

Artificial intelligence (AI) is rapidly transforming the labour market, bringing both opportunities and challenges. While AI has the potential to automate tasks and eliminate jobs, it can also drive innovation, productivity growth, and economic growth. To fully reap the benefits of AI, while ensuring a fair and inclusive transition, investments in education, training and proactive policies are needed. Addressing the ethical and social implications of AI on the labour market will also be crucial to ensure that technological advances serve the interest of society at large. By engaging in informed debate and collaboration among stakeholders, we can shape the future of work in the age of artificial intelligence in a way that promotes prosperity and good work practices for all. In addition to the positive aspects or advantages that digitalization, digital transformation and artificial intelligence offer, there are also disadvantages on the other side of the scale. Scientists from the University of Oxford (Carl Benedict Frey and Michael Osborn) conducted a study examining the effect of computerization on 702 professions, thus concluding

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that 47% of existing jobs in the US, 35% in the UK and 49% in Japan were at risk of liquidation, as a result of automation in the next two decades, in particular, in areas such as logistics, transport, trade and services. According to their findings, it is expected that, by 2040, computers will be able to conduct mathematical research, perform surgery, write novels and other activities that will become independent of human resources.

Also, it should be emphasized that a company's high productivity does not necessarily translate into an increase in performance, as investments in digitalization impose high costs on companies, which is understood as a negative impact on the financial performance of companies in the short term (Chen and Srinivasan, 2020). In another approach, Salvi et al. (2021) showed that the information provided by companies regarding their level of digitalization has an impact on the expectations of potential investors regarding future cash flows, being justified by the ability of these companies to generate higher cash flows, in close connection with cost reduction and revenue growth.

3. Data and Methodology

The research methodology used in the present work consists in applying of Gaussian Graphic Models (GGMs), which represent an econometric method, with a visual component, used in the study of relationships between variables, where edges represent conditional dependencies between pairs of nodes. These models are used to identify conditional dependencies between variables, having applicability in various fields such as economics, demography, biology and genetics (Anandkumar et al., 2012). This study used annual data from 2011-2022 for the EU countries, obtained from the Eurostat (European Commission, 2023).

The GGM model, estimated in this work, is based on the partial correlation algorithm – PCOR, in identifying the intensity of links between variables (thickness of the link), but also the influence between them (blue - positive, red - negative).

GGM models provide a stable framework for estimating partial correlations, measuring conditional dependencies between variables and offering the possibility of visualizing the results in the form of a network of nodes, which represent variables, as well as dependencies between variables in the form of edges or edges (Roverato, 2017). Equally important, the absence of an edge corresponds to conditional independence of two variables, given the remaining variables.

To analyze the dynamics and impact of economic and social transformations in the context of digitalization, the econometric models developed in this paper include the following indicators presented in the table below. These indicators are fundamental in understanding the complexity of the relationships between digitalization and socio-economic progress.

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The indicators used in the econometric models, collected and individualized for each of the EU-27 Member States, are classified as follows:

- *the group of representative indicators for infrastructure and digital capital*, consisting of 8 variables, including: Connectivity (conec), Human capital (human_capital), Degree of integration of digital technology (int_teh_dig), Public digital services (services_dig_pub), Labour productivity per person employed (prod), Employment rate, 15-64 years (ra_15_64), Labour productivity per employed person (prod) and unemployment rate in the 15-64 age group (rs_15_64);

- *the group of representative indicators for innovation and socio-economic impact* includes an equivalent number of variables, namely: Government budgetary allocations for research and development, according to socio-economic objectives (agbcd); Human resources in science and technology (rust); Internet access level per home (acces_net); High-speed Internet coverage by area (net_rapid); People with ICT (Communication and Information Technology) education by state on the labour market (tci_edu); Specialists TCI employed – total (tci_pec); Digital Economy and Society Index (iesd_total); and Human Development Index (idu).

Table 1.Descriptive statistics of variables used in econometric model

Variables	Obs.	Average	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
conec	11	37.58	12.79	12.67	77.09	3.08	0.66
human_capital	11	45.56	9.26	27.48	71.39	0.38	2.76
int_teh_dig	11	29.46	10.26	10.12	59.09	0.42	3.04
services_dig_pub	11	57.31	16.50	7.41	91.18	-0.47	3.20
prod	11	97.52	30.72	46.2	224.8	1.65	6.74
rs_15_64_ani	11	4.35	1.98	1.3	13	1.74	7.01
ra_15_64_ani	11	69.29	5.70	53.2	81.8	-0.60	3.02
prod	11	97.52	30.72	46.20	224.8	1.65	6.74
agbcd	11	4.35	1.98	1.3	13	1.74	7.01
rust	11	0.549	0.23	0.14	1.12	0.06	2.05
acces_net	11	48.5	9.00	27.7	69.2	-0.08	2.31
net_rapid	11	57.39	27.01	0	100	-0.38	2,18
tci_edu	11	4.37	1.35	2	8.6	0.73	3.23
tci_spec	11	4.37	1.35	2	8.6	0.73	3.23
iesd_total	11	93.59	4.44	73.6	100	-1.74	6.59

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idu	11	0.89	0.03	0.81	0.96	-0.45	2.67

Source: own processing using the econometric package Stata 18, based on Eurostat data (European Commission, 2023)

Analyzing the descriptive statistics in Table 1, a significant variety can be observed among the studied variables, which reflect different aspects of technological and economic progress. Connectivity (conec) shows a relatively large standard deviation and a strongly positive symmetry, indicating a right-skewed distribution, with some extremely high values compared to most observations for the period 2011-2022, at the level of EU Member States-27. Human capital (human_capital) and digital technology integration (int_teh_dig) show less variability and an almost symmetrical distribution, suggesting a relatively even dispersion of the data around the mean.

Public digital services (services_dig_pub) and labour productivity (prod) also have significant variation, with prod showing a pronounced positive symmetry and a pronounced curvature, signaling the presence of extreme values. The employment rate in the 15-64 age group (ra_15_64) demonstrates a more compact distribution and slightly negative symmetry, indicating a concentration of data around a higher mean value. For the unemployment rate in the 15-64 age group (rs_15_64) it can be seen that it has a mean value of 4.35 and a standard deviation of 1.98, indicating a relatively high variability. The distribution is highly skewed, with a skewness coefficient of 1.74 and a very high skewness of 7.01, suggesting a heavy-tailed, heavily peaked distribution. Labour productivity per employed person (prod) shows a high dispersion based on the data estimated in Table 1 and a strongly asymmetric distribution.

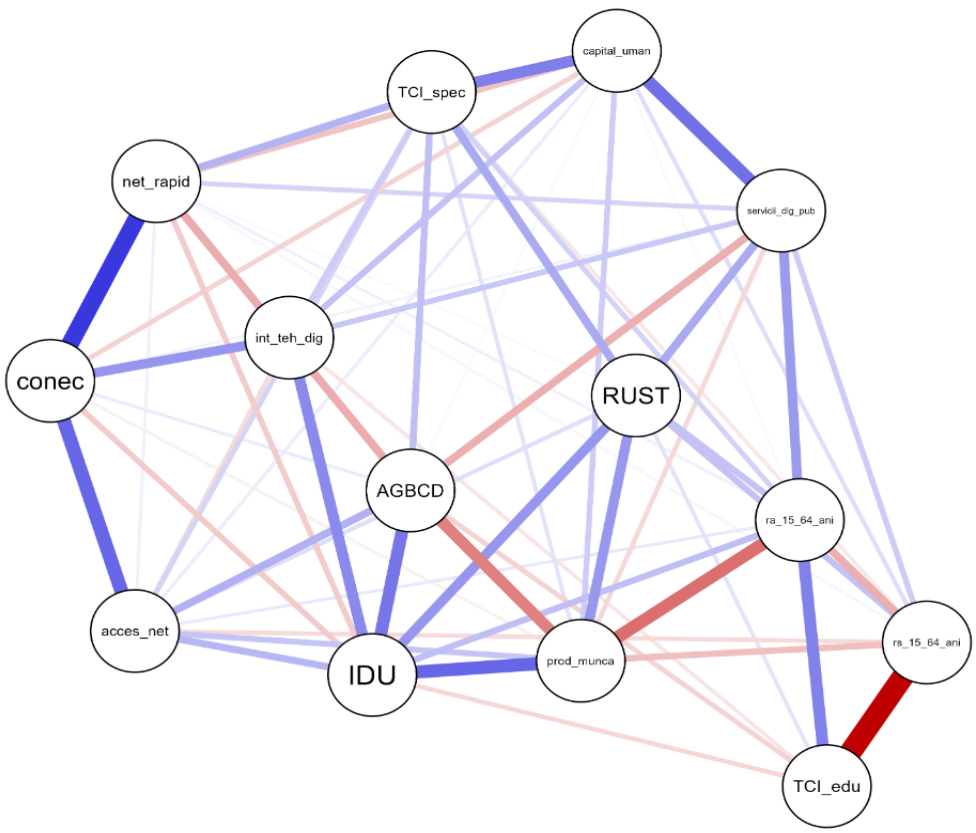
Government budget allocations for research and development (agbcd) show very high skewness, signaling a concentration of observations either around the mean or at the extremes, with a few exceptionally large values tending to skew the distribution. Internet access (acces_net) and fast internet rate (net_rapid) illustrate a relatively normal distribution with moderate standard deviations and symmetries close to zero. The analysis of ICT education (tci_edu) and ICT specialists (tci_spec) shows consistency in the data, with identical standard deviation and positive symmetry, suggesting a tendency for the data to cluster towards values higher than the mean. The digital economy and society index (iesd_total) and internet usage density (idu) reflect different aspects of digitalisation, with iesd_total showing a strong negative symmetry, indicating the presence of countries with particularly high digital performance.

Descriptive statistics highlight the diversity of technological and economic conditions between Member States, with significant variabilities in terms of connectivity, human capital, and innovation, suggesting the need for targeted policies to address disparities and boost inclusive growth.

3. Results and discussions

The Gaussian Graphical Model (GGM) estimated in Figure 1, with a visual graphical component, includes the components of the digital economy and society index, namely (conec, human_capital, int_teh_dig and services_dig_pub), as well as a series of indicators representative of infrastructure and digital capital (int_teh_dig, prod, ra_15_64, rs_15_64) and representative indicators for innovation and socio-economic impact (agbcd, rust, acces_net, net_rapid, tci_edu, tci_spec, idu). The graphical representation swoed in Figure 1 consists of nodes and the links between these nodes, which indicate interdependence relationships. Strong relationships are marked by thicker or darker lines, while weaker relationships are represented by thinner or lighter lines.

Figure 1. The Gaussian Graphical network (GGM) resulting from the estimation of the econometric model for the influence of digitalization on the labour market, at EU-27 level (2011-2022)



Source: own processing using the econometric package Stata 18, based on Eurostat data (European Commission, 2023)

ISSN: 2455-8834

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Gaussian Graphical Model estimation reveals a strong relationship between connectivity (conec), degree of integration of digital technology (int_teh_dig), level of internet access per home (acces_net) as well as high-speed internet coverage by area (net_rapid), indicating that better connectivity is associated with greater integration of digital technology and wider Internet access. Human capital (human_capital) is strongly connected with public digital services (dig_pub_services), suggesting that higher levels of human capital may be correlated with more developed digital public services. Also, the relationship between human capital (human_capital) and the TCI specialists (tci_spec) is positively marked. Similar results were presented by the author Mihăilă (2022), who supports the idea that specialized human resources can add value in the digital age.

The relationship between labour productivity (prod) and the employment rate, 15-64 years (ra_15_64) is strongly and negatively marked, meaning that higher labour productivity could be associated with a lower employment rate in the specified age category, also there is a negative relationship between labour productivity and the government budget allocations for research and development (agbcd). Savelieva (2019) claims that there is a direct relationship between labour productivity and the employment rate, as the results of this analysis show.

As we can see, human development index (idu) has a lot of positive influences on several variables like labour productivity (prod), government budget allocations for research and development (agbcd), the degree of integration of digital technology (int_teh_dig), and human resource in science and technology (RUST), these connections show that the more a country invests in human development, the more progress is made in this country in terms of labour productivity and access to technology is easier.

Equally, a series of negative relationships can be observed between government budget allocations for research and development (agbcd) and labour productivity (prod), but also the degree of integration of digital technology (int_teh_dig), suggesting that a low level of government allocations can strongly negatively affect labour productivity and the degree of integration of digital technology.

5. Conclusion

As the world continues to embrace digital technologies and the pace of digital transformation accelerates, it is crucial to understand the impact of these developments on the economy and society. By conducting a comprehensive analysis of the effects of digitalization and digital transformation on the EU Member States, this paper seeks to contribute to the ongoing understanding of this phenomenon, therefore, the results of this research will contribute to a better understanding of the complex interplay between digital advancements and their socio-economic consequences, providing valuable insights for policymakers, businesses, and researchers.

Following the econometric analysis carried out, as well as the review of the official publications of the European Commission on this subject, I consider appropriate the following proposals for measures that could contribute to increasing the results in the field of digitalization: investing in digital infrastructure, digital education and training, boosting innovation and research, simplification of administrative procedures, tax incentives for the adoption of digital technologies, granted to companies investing in digital technologies, collaboration and exchange of best practices between EU Member States.

Investments in infrastructure, education, support for SMEs, favourable regulations, research and a robust entrepreneurial ecosystem are essential to ensure that Member States will be better prepared to face the challenges of the digital future and to take advantage of the opportunities offered by emerging technologies.

One of the limitations of this research is the lack of data, the fact that are not available data for several representative indicators for digital economy and society and there are not enough data available at the level of 2023, for the analysis to be even more current.

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