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The Faculty of Theoretical and Applied Economics

**Economic convergence
in European Union
(ECEU)**

**The Future of Economics:
AI's Disruptive Potential**

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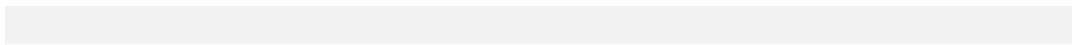
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Artificial Intelligence as a human capital multiplier: a new economic paradigm

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Abstract. *Artificial intelligence (AI) is increasingly perceived both as an opportunity to increase productivity and as a disruptive factor in the traditional labor market. This study analyzes the impact of AI adoption on employment dynamics in the European Union, investigating whether automation leads to job substitution or, on the contrary, to increased efficiency. Using economic data from various sources such as Eurostat, OECD, we compare countries with a high degree of AI implementation (e.g. Cyprus, Ireland) with those where the process is slower and more difficult to implement. Through an empirical approach based on linear regressions and econometric methods, the results indicate that sectors integrating AI alongside the development of digital skills register significant increases in productivity, without having a negative impact on the employment rate. The conclusions underline the importance of adopting public policies focused on reskilling the workforce as well as regulating the AI area of action, so that the benefits are distributed equitably.*

Keywords: Artificial Intelligence (AI), economic productivity, human capital, labor market, digitalization.

JEL Classification: A1, F62, I24, P51.

Introduction

The accelerated development of artificial intelligence in the last decade has profoundly reconfigured both the dynamics of labor markets and the way organizations function. For companies, the strategic investment in human capital, specialized in artificial intelligence, becomes an essential factor in capitalizing on the potential of these emerging technologies and in consolidating the competitive advantage. (Eisfeldt, et al., 2023)

While the overall benefits of AI adoption, such as increased productivity and innovation, are well documented, the literature provides a fragmentary picture of the concrete impact of AI inspirational investments on the internal functioning of firms, especially in terms of the efficiency of data processing processes. (Burstein, 2014)

The profound transformations generated by technological progress have led to a long debate on the role of artificial intelligence at the heart of the economy and the global social impact. With the expansion of the applicability of artificial intelligence in sectors such as health, industry, education, services or even politics, it becomes clear that this technology not only automates tasks but also redefines the very nature of work, capital and added value.

Artificial intelligence is today more than just a digital tool, it is identified as a multiplier of human capital, capable of amplifying cognitive skills, optimizing decision-making and accelerating innovation. Some opinions and perspectives claim that artificial intelligence will replace jobs, accentuate inequalities and diminish the importance of the human factor. But more and more studies and research suggest that, when used responsibly, this tool can complement, not just replace human capital, and create a new type of collaboration that generates added value superior to the positions at stake.

This paper aims to analyze how artificial intelligence works as a multiplier of human capital, defining the professional roles, organizational models and prospects for economic development perspectives. The study aims to conceptually and empirically substantiate the emergence of a new economic paradigm, in which the interaction between people and technology becomes an essential link to increase competitiveness and innovation among employers and companies on the market. By using quantitative methods, it aims to identify significant relationships between the degree of integration of artificial intelligence in organizations, as well as the level of qualification of the workforce and economic performance indicators. The study contributes to understanding how the interaction between people and technology shapes the emergence of new economic models, centered on the complementarity between human skills and digital capabilities. (Acemoglu & Autor, 2011)

In this case, the research question arises: (RQ1) To what extent does the integration of artificial intelligence in the organizational environment contribute to the multiplication of human capital and to the stimulation of economic performance? The answer to this research question aims to provide a deeper understanding of how artificial intelligence redefines skills and productivity in the new digital economic context. The integration of artificial intelligence into work processes contributes positively to increasing performance, by capitalizing on and expanding the skills of human capital. The eligibility of the research hypothesis is verified here: Companies that invest in the development of employees' digital skills achieve superior benefits with the use of AI. (H1)

This paper uses a comparative approach between several European countries to analyze the impact of artificial intelligence as a factor of multiplication of human capital. Quantitative data from official sources (Eurostat, OECD) and academic studies are used. Econometric methods and comparative graphs are used. And the goal is to identify trends and differences regarding the integration of artificial intelligence in the economy and at the level of human resources. (Acemoglu, 2019)

Literature review

In the current economic context, characterized by uncertainty, volatility and intensified global competition, competitive advantage no longer derives only from the use of human resources or cheap labor, and from the ability to capitalize on the synergy between technology and human potential.

According to the World Economic Forum held in 2023, companies that adopt human-artificial intelligence collaboration models are seeing more significant increases in productivity and satisfaction among employees and customers. Thus, artificial intelligence becomes a strategic tool and a competitive advantage, supporting employees to be more efficient, more creative and more adapted to the requirements of the digital economy. At the same time, this transformation brings with it ethical, social and organizational challenges. (Modestino, 2019)

However, we still do not have a solid and complete theoretical framework that integrates both the automatic effects of new technologies and possible compensatory mechanisms. The need to develop such a framework stems not only from the importance of understanding how and when automation will reshape the labor market, but also from the fact that similar predictions have been made in the past without fully realizing. For example, Keynes anticipated, as early as 1930, that technological progress would lead to a steady increase in incomes, but also to widespread technological unemployment, generated by the replacement of human labor by machines, an estimate that later turned out to be largely inaccurate. (Keynes, 1930)

Artificial intelligence is currently one of the most promising and threatening emerging technologies, with extensive potential applications in numerous economic sectors and functional areas. While AI has the potential to significantly boost productivity and generate new job opportunities, it can also replace the human workforce in order to reduce costs in the long- term among large companies. (Acemoglu & Restrepo, 2018)

This technological substitution can lead to a decrease in the share of work in the economy, an increase in social inequalities, (Acemoglu, 2018) as well as significant disruptions in various industries. (Mateos-García, 2019)

For this reason, the impact of AI is a topic of major interest for both economists and policymakers, especially in the context of economies facing stagnant productivity and shrinking active population.

However, the actual level of adaptation of AI at the organisational level, its penetration into different occupations and the concrete effects on the labour market remain largely insufficiently documented. (Anghion, 2019)

In the context of accelerated technological developments, it is also essential to take into account the demographic and generational changes that shape the structure of the labour market. The new generations entering the labor market, especially Generation Z and Millennials.

They are distinguished by an increased familiarity with technology and a natural inclination towards digital skills. This redefines the human profile needed in today's economy, as the demand for advanced digital skills becomes more pronounced, both in traditional sectors and in emerging industries. Thus, digitalization is not just a technological trend, but a process supported by profound cultural and educational transformations, which require the continuous adaptation of training and professional integration strategies. (Schwieger, 2018)

Methodology

Given the main purpose of this analysis, a comparative case study approach was adopted to assess the impact of AI on various macroeconomic indicators, such as: labor productivity, the level of investment allocated in the ICT industry, recorded in the period 2015-2023. In this analysis, several European states were selected.

The main criterion for the analysis of these indicators was the impact of AI found at the level of the labor market within several states. A few countries have stood out in a positive way, having a wider openness to the regulation and innovative application of this technological tool, and other countries are facing challenges generated by the lack of digital education, in this context. (Lin, 2011)

This research methodology used a quantitative analysis focused on econometric modeling to compare the effects of the implementation of artificial intelligence in different fields within these states. The first step was to use several econometric, complementary models such as regressions and cointegration tests. To identify cause-and-effect links, the data was collected for a recent period of time, given the impact of artificial intelligence that has experienced a significant growth in the last five years. The data were taken from both international and national databases, Eurostat was used for the analysis of indicators specific to European countries, and the Romanian Institute of Statistics for national data. The analysis of these data was carried in Microsoft Excel 2019, where descriptive data were generated for all the mentioned variables. In addition, other software was used for the generation of table and figures (EViews 12), statistical analysis and econometric modeling (IBM SPSS Statistics).

However, the study carried out has certain limitations generated by external causes, such as the lack of data availability, due to the recent period of expansion of artificial intelligence, we have a limited period of time in terms of data collection. Another problem is the limitation of the sample size. We have chosen to focus only on certain countries to show the discrepancies between the states that invest in digital education and regulate it

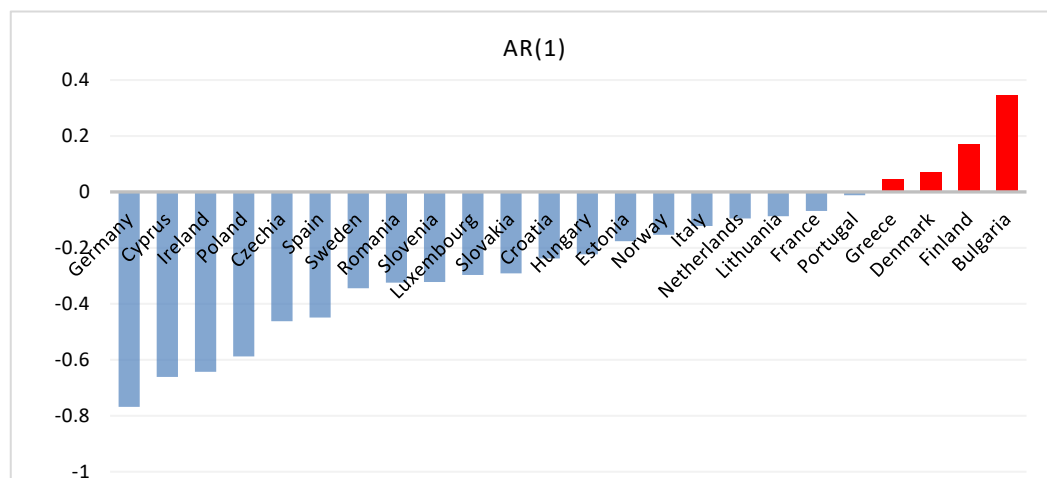
and the states that face problems in terms of digital education. However, the limitations reflect a possible future expansion of this work.

Results and discussions

This chapter systematically presents the main results of the research, by integrating the quantitative analyses performed and the critical interpretation of the relationships identified between the analyzed variables, as well as the validation/refutation of the hypothesis formulated above. Also, the similarities or differences obtained from the specialized literature are discussed, focusing on the current European context, marked by accelerated digitization and an active presence of regional disparities. Various methods were used, such as linear regression analysis, cointegration tests and analyses carried out in terms of graphical representations in the context of the digital transition at European level.

To capture the complexity of the phenomenon studied, the research included both a long-term analysis over several years and a comparison between states with a focus on the structural differences between the countries of Central and Eastern Europe and those of Northern and Western Europe. Also, applying tests such as Pedroni and Phillips-Peron to verify the existence of a long-term cointegration relationship between the

Figure 1. *Distribution of correction mechanisms*



Source: Authors' own research via EViews

Even though the R^2 value is 0.063, which means that only 6.3% of the productivity variation is explained by the share of Capital, the global test of the model ($F=15.70$, $p<0.001$) shows that the model is statistically significant, so the share of capital has a statistically significant impact on the level of labor productivity, even if the effect is limited.

Table x shows the 10 most sought-after tech jobs for 2025, according to the report. From the analysis of the list, the global trend of accelerated digitization and transformation of the labor market is clearly observed, where the demand for advanced IT skills becomes essential.

Table 1. *Top Careers 2025*

The Top 10 Most In-demand Tech Careers for 2025	
1.	Artificial Intelligence (AI) and machine learning engineers
2.	Data analysts and scientists
3.	Cybersecurity analyst
4.	Cloud engineers
6.	DevOps engineers
7.	Full stack developers
8.	Blockchain engineers
9.	UX/UI Product Designers
10.	Product Managers

Source: Report (Liebenberg)

At the top of the ranking are specialists in artificial intelligence and machine learning, which confirm the current direction of automation and use of algorithms in multiple economic sectors.

Table 2. *Model Panel with fixed effects estimated by EGLS: Analysis of the relationship between the level of capital and labour productivity in EU Member States*

Method: Panel EGLS (Cross-section weights)

Date: 04/15/25 Time: 12:19

Sample: 2015 2023

Periods included: 9

Cross-sections included: 26

Total panel (balanced) observations: 234

Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	104.3118	0.297436	350.7033	0.0000
ICT_CAPITAL	1.22E-07	1.72E-07	0.707512	0.4800
Effects Specification				
Cross-section fixed (dummy variables)				
Weighted Statistics				
R-squared	0.440105	Mean dependent var	1537.250	
Adjusted R-squared	0.369780	S.D. dependent var	3799.919	
S.E. of regression	6.673180	Sum squared resid	9217.984	
F-statistic	6.258149	Durbin-Watson stat	2.345932	
Prob(F-statistical)	0.000000			
Unweighted Statistics				
R-squared	0.191825	Mean dependent var	104.5221	
Sum squared resid	10432.52	Durbin-Watson stat	2.360175	

Source: Authors' own research via EViews.

According to this model, the labor productivity per employee, registered in a company with +250 employees, is not entirely influenced by the level of capital found in the ICT institution, because these investments do not directly and immediately generate productivity, and capital regardless of its nature without complementary human skills remains at an underutilized level. These results can be perceived as a lagged effect of increasing investment in the digital industry in employee productivity.

This analysis highlights the role of the employee as a multiplier of technology, because technology alone does not bring performance, but combined with human skills.

Table 3. *Pedroni Panel Cointegration Test for the productivity-Capital relationship in EU countries*

Pedroni Residual Cointegration Test				
Series: W_PERSON ICT_CAPITAL				
Sample- YEARS: 2015 2023				
Included observations: 234				
Cross-sections included: 24 (2 dropped)				
Newey-West automatic bandwidth selection and Bartlett kernel				
Alternative hypothesis: common AR coefs. (within-dimension)				
	Weighted			
	Statistical	Prob.	Statistical	Prob.
Panel v-Statistic	-0.864011	0.8062	-2.766763	0.9972
Rho-Statistical Panel	-0.664036	0.2533	0.516862	0.6974
PP-Statistical Panel	-12.75144	0.0000	-12.08960	0.0000
ADF-Statistical Panel	-3.426927	0.0003	-6.132614	0.0000
Alternative hypothesis: individual AR coefs. (between-dimension)				
	Statistical	Prob.		
Group rho-Statistic	2.399804	0.9918		
Group PP-Statistic	-18.05115	0.0000		
Group ADF-Statistic	-5.257426	0.0000		

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
Austria		Dropped from Test			
Belgium		Dropped from Test			
Bulgaria	0.344	1.74E-06	1.00E-06	4.00	8
Croatia	-0.238	2.588046	0.354916	7.00	8
Cyprus	-0.661	0.412531	0.401995	2.00	8
Czechia	-0.462	1.056068	1.056068	0.00	8
Denmark	0.011	3.308040	0.602513	7.00	8
Estonia	-0.172	4.216548	3.540969	2.00	8
Finland	-0.184	6.558447	6.716501	1.00	8
France	-0.068	11.39553	1.718619	7.00	8
Germany	-0.768	9.853631	2.597438	7.00	8
Greece	0.046	13.93879	3.768369	7.00	8
Hungary	-0.123	22.69004	5.485395	7.00	8
Ireland	-0.643	23.50919	26.63685	1.00	8
Italy	0.032	12.21956	5.679538	4.00	8
Lithuania	-0.087	75.81922	59.82099	2.00	8
Luxembourg	-0.719	25.14607	3.912347	7.00	8
Netherlands	-0.095	36.61630	7.953937	6.00	8
Norway	-0.153	75.99702	105.5011	1.00	8
Poland	-0.588	34.64877	29.34744	1.00	8
Portugal	-0.012	41.61610	7.408017	7.00	8
Romania	-0.324	63.50981	48.28635	3.00	8
Slovakia	-0.291	74.58540	70.73727	1.00	8
Slovenia	-0.322	75.52395	14.07993	7.00	8
Spain	-0.449	66.22861	18.32432	6.00	8
Sweden	-0.344	75.08572	75.08572	0.00	8

Source: Authors' own research via EViews.

We also used this Pedroni cointegration test, specific to panel data, to investigate whether there is a long-term equilibrium relationship between productivity and ICT investments, over a recent period from 2015-2023, the investigated sample comprising the 24 European countries.

General test results:

PP-Statistical: -12.15, $p=0.000$;

ADF- Statistical: -3.42, $p=0.0003$

PP-Statistical: -18.05, $p=0.0000$

These values indicate the rejection of the null hypothesis of non-cointegration, which means that the variables are cointegrated and evolve together over time, in the long term. The relevance of the test is high, given the robustness and consistency of the statistics between the two dimensions (within and between).

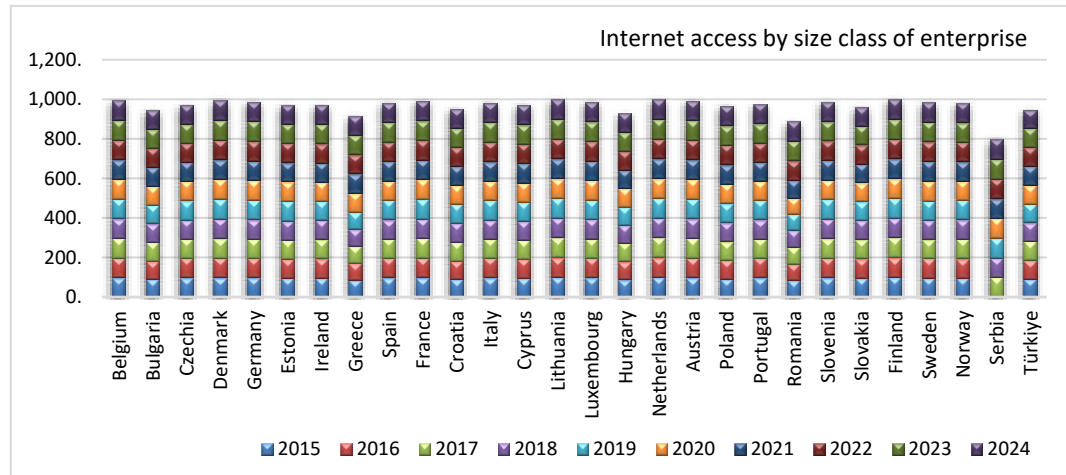
We extended the analysis by particularizing for countries: The case Cyprus, where AR (1): -0.661, HAC: 0.401995, matching the observations from the period 2015-2023. Cyprus has the strongest negative AR coefficient, which indicates a rapid correction of equilibrium deviations. The extremely low HAC value reinforces the idea of a stable model.

Ireland has the values AR (1): -0.643, HAC: 26.63, although the HAC is higher than in the case of Cyprus, the adjustment coefficient suggests a solid relationship between the variables.

At the opposite pole are states that do not emphasize the integration of investments in the ICT domain, and productivity decreases considerably due to the lack of existing regulation. A relevant example is Bulgaria, AR(1): 0.344, HAC: 1.00, where the positive coefficient suggests the absence of cointegration, although the HAC value is very small. The correlation errors does not occur, indicating an unstable relationship. And Hungary, AR (1): 0.223, HAC:5.48, suggests a positive coefficient and highlights an unstable relationship, which does not present stable evidence for a clear relationship of convergence between variables.

The results of this test indicate a cointegration relationship between productivity and the level of capital recorded across the entire panel. However, the differences between countries are significant, suggesting that national policies and efficiency in the use of capital directly influence the stability of the relationship in the long term. The Nordic countries and Cyprus provide examples of good practice, while Eastern European countries may report structural gaps and inefficient investments.

The graph highlights the degree of internet access among European companies, differentiated according to their size, as well as the significant disparities existing between different member states of the European Union. The analysis highlights the obvious regional discrepancies between Western and Northern European countries, which have achieved a high level of connectivity, and Central and Eastern European countries, where connectivity still remains below potential, especially in the case of small firms. Countries such as Finland, Denmark and Switzerland have recorded connection rates of up to 100%, demonstrating not only solid digital infrastructure, but also coherent public policies in support of the digital transformation of the business environment.

Figure 2. *Internet access for businesses in the EU, by size and country, 2015-2024*

Source: Authors' own computation from Eurostat database.

On the other hand, countries such as Romania, Bulgaria or Croatia have lower levels, which suggests the existence of structural barriers: lack of investment in technology, limited access to digital training or high connection costs.

Moreover, the evolution of connectivity over the last decade reflects the general dynamics of the digitalization of the European economy, but also the persistent gaps in the member states. While there is a general trend of increasing internet access, the pace of this progress varies considerably, raising questions about digital cohesion at European level.

Conclusion

Studies amplify the fact that AI-based technologies act as a multiplier for human capital, boosting efficiency and productivity at the individual and organizational level. By automating repetitive tasks and optimizing workflows, AI allows employees to focus on activities that require creativity and critical thinking. The benefits offered by AI are conditioned by the geographical space, the legislative context of regulation and adoption, as well as the professional training of the workforce for digital purposes.

The study also underlines the importance of government interventions and education policies in facilitating the transition to a digital economy.

One of the main limitations of the study is the lack of a data set that fully reflects the true scale of AI adoption, as companies can access AI expertise through various channels that are not currently prominent. Partially available or fragmented data can influence the accuracy of estimates of the effects of AI on human capital. For example, companies can purchase externally developed algorithmic solutions or build AI skills within existing teams. However, even in these cases, the role of human capital remains essential: internal employees are needed to function as multipliers, they facilitate the integration of AI technologies by adapting them to the needs of organizations, preparing and preserving data, maintaining systems and training colleagues for the efficient use of the new tools to be implemented.

This study can be extended together with the analyses carried out to other industries, becoming essential to investigate how these technologies influence employment dynamics, income distribution and the level of socio-economic inequalities.

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Redefining state intervention in the economy: state aid in the Era of Artificial Intelligence

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Abstract. *This paper explores the potential for integrating artificial intelligence (AI) into state aid management, focusing on improving efficiency, transparency, and accountability in the public and privat sector. The study employs a conceptual and legal-institutional analysis, complemented by a qualitative case study on Romania, based on the 2021 World Bank evaluation. It highlights how AI can support decision-making, risk monitoring, and the equitable distribution of funds and specific AI technologies and algorithms support strategic management of state aid. Best practices from other EU Member States (e.g., Estonia, the Netherlands) are presented, along with policy proposals for the effective integration of AI into state aid schemes.*

The digital revolution has been underway for some time, and Artificial Intelligence (AI) is not only redefining operational processes but also prompting a strategic reconfiguration of the role of the state in the economy and the financial support allocated from the European budget entails responsibilities regarding ethics, transparency, and compliance with European regulations.

Keywords: state aid, artificial intelligence, digital governance, strategic public management, algorithmic transparency.

JEL Classification: H11, L38, M48, O33, D73.

1. Introduction

State aid is a key public policy instrument through which governments support certain economic sectors, regions, or enterprises, aiming to foster development and correct market imbalances. In the European Union, such interventions are regulated under Article 107 of the Treaty on the Functioning of the EU. As a Member State, Romania has adopted numerous state aid and de minimis schemes to support the private companies and strategic sectors, particularly in the context of post-pandemic recovery. However, administrative complexity, large volumes of data, and risks of fraud or conflicts of interest hinder implementation efficiency.

The state has become a central pillar in the strategies of the private companies, fundamentally transforming contemporary economies and societies, as well as the way organizations manage operations, process data, and innovate. The development of a European ecosystem that supports research excellence and responsible, inclusive, and secure innovation is proposed, alongside emphasizing the need for public resource allocation in key areas such as data infrastructure, testing platforms, algorithm development, and supporting private companies in adopting AI technologies.

This transformation is not merely a passing trend but a phenomenon that challenges the traditional role of the state in the economy and redefines public interventions, particularly state aid, to promote innovation and competitiveness in an equitable manner, positively influencing the operations of private companies.

The White Paper on Artificial Intelligence, published by the European Commission in 2020, emphasizes the need for an approach based on "excellence and trust" in the development of AI, highlighting both the opportunities (such as increased efficiency in public services and economic benefits in sectors like healthcare and transportation) and the associated risks, including the automation of technical processes and advanced data analysis (European Commission, 2020).

Analyzing the data contained in the White Paper reveals the necessity of creating a European ecosystem to support research excellence and responsible, inclusive, and secure innovation. This effort requires significant public investment in key AI domains such as data infrastructure, testing platforms, algorithm development.

In this context, state aid becomes a strategic public policy tool, directed towards supporting projects with high added value and positive disruptive potential.

Public aids can cover the costs of implementing AI systems, acquiring software licenses, developing internal intelligent applications, or training personnel to use new automated solutions. In this way, the state supports not only operational efficiency but also a faster and safer transition towards a data-driven business model.

2. Literature review

The European Context and the Role of AI

At the European level, the digitalization of public administration is a strategic priority. The White Paper on Artificial Intelligence (European Commission, 2020) promotes the development of trustworthy AI, focused on respecting fundamental rights and supporting innovation. In the context of state aid, AI can enable predictive allocation of resources, automatic detection of irregularities, and enhanced transparency through integration with platforms such as the Transparency Award Module (TAM).

In this context, state aid becomes a strategic tool of public policy, directed towards supporting projects with high added value and disruptive potential. For instance, funding through Important Projects of Common European Interest (IPCEI) allows Member States to support major initiatives in fields such as microelectronics and cloud computing, essential for the AI ecosystem (Hornkohl & Pelekis, 2025).

The General Block Exemption Regulation, extended under the Treaty on the Functioning of the European Union (TFEU, Article 107), allows for the granting of aids for digitalization, research, and innovation. Companies can benefit from grants, tax incentives, and other support measures for adopting and integrating AI, developing proprietary solutions, and reskilling employees (European Commission, 2023). These measures are regulated within the European Union's legal framework, particularly under Article 107 of the TFEU, which establishes the conditions under which state aid is deemed compatible with the internal market (European Union, 2016).

This dynamic underlines a paradigm shift: state aid is no longer merely a tool for correcting market failures but a vehicle for economic transition and digital transformation. The state thus becomes an active partner of companies in building a knowledge-based, data-driven, and algorithmically responsible economic model. State aid policies in the AI era express a new economic governance model – proactive, targeted, and anchored in the European values of inclusion and digital sustainability.

Access to AI-related state aid schemes can represent a significant competitive advantage for private companies, reducing investment risks and promoting the development of niche competencies that differentiate them in the interconnected global economy. At the same time, this support implies ethical responsibilities, transparency, and compliance with European regulations on state aid and data protection.

3. Methodology

The paper is based on a conceptual and legal analysis of EU and Romanian regulations on state aid. This is complemented by a case study on Romania, using data from the "Design for Impact" report (World Bank, 2021) and examples of best practices from other EU countries. Qualitative methods are used, including content analysis, policy comparison, and assessment of the strategic framework for digital governance.

4. Results and discussions

The use of AI in advanced research not only accelerates data collection and interpretation but also enables companies to identify growth opportunities ahead of competitors, optimize investments, and mitigate exposure to risks. Whether discussing economic forecasts, consumer behavior analysis, or the anticipation of geopolitical events, AI-based systems become indispensable allies in making informed and timely decisions.

Through fiscal incentives, co-financing, or non-repayable grants, governments can accelerate AI adoption in fields such as predictive analysis, risk assessment, or portfolio optimization. Thus, state aid directly contributes to strengthening enterprises' analytical capacity and their competitive positioning on global markets.

Machine learning algorithms can analyze massive volumes of historical data, identifying patterns and trends that may elude human analysis.

The Contribution of AI

State aid programs – government grants, subsidies, and incentives to support economic and social objectives – involve complex decision-making and oversight. Managing these programs strategically is challenging due to the volume of applications, the need for fair and transparent selection, risks of fraud or double funding, and the pressure to maximize economic impact. Artificial intelligence (AI) offers powerful tools to enhance each stage of state aid administration. From automating project selection based on clear criteria to detecting fraud patterns, monitoring projects in real time, and simulating policy outcomes, AI can help managing authorities and private companies to make better decisions and ensure public funds are used effectively. The sections below detail how specific AI technologies and algorithms support strategic management of state aid, along with examples of current implementations (notably in EU and OECD countries).

Artificial intelligence can directly support strategic management by:

a. Automating the selection process for eligible projects based on transparent criteria:

Selecting which projects to fund typically requires evaluating eligibility and merit against a checklist of criteria. AI can automate much of this initial screening in a transparent and rule-based manner. One approach is using *expert systems* or rule-based algorithms that apply the same criteria a human evaluator would – for example, ensuring the applicant meets all formal requirements (sector, size, co-funding share, etc.) and that the proposal aligns with program objectives. These systems effectively turn funding guidelines into code, so every decision is traceable to a clear rule, bolstering fairness and transparency. In practice, many funding agencies already use automated checklists to filter applications: a recent proof-of-concept in a European public administration showed an AI system reviewing funding applications against an eligibility checklist, marking which criteria were satisfied or not, and flagging borderline cases for human review.

b. Early detection of fraud risks and double funding through pattern recognition algorithms:

Once projects are selected and funds disbursed, authorities must safeguard against misuse of funds – including fraud, corruption, or double funding (the same expense being paid

twice from different sources). AI excels at pattern recognition in large datasets and can flag irregularities far earlier and more reliably than traditional audits. One technique is anomaly detection, where unsupervised ML algorithms establish baseline patterns of legitimate behavior and then identify outliers. For example, AI systems can continuously scan claims and transactions to pinpoint anomalies such as suspicious timing or amounts – e.g. multiple reimbursement claims just under a threshold that normally triggers extra scrutiny

Catching such patterns (possibly indicative of someone intentionally splitting invoices to evade controls) in real time allows investigators to intervene before fraud escalates.

c. Real-time monitoring of project implementation with automated alerts:

Beyond preventing outright fraud, AI can assist in monitoring the implementation of funded projects to ensure they stay on track with timelines, budgets, and intended outcomes. Traditional monitoring often relies on periodic reports and infrequent site visits, which means problems (delays, cost overruns, deviations from objectives) might be detected late. It's important to note that human oversight remains crucial. AI can augment monitors by filtering noise and pointing to likely issues, but project officers will still investigate and decide on corrective actions.

c. Providing decision support for managing authorities through simulations and economic impact predictions:

Strategic management of state aid isn't only about managing individual projects; it's also about big-picture decision support – planning allocations, designing programs, and adjusting policies for maximum impact. AI can play a transformative role here by providing simulations and forecasts that inform policy choices.

One exciting application is AI-driven policy simulation. Traditionally, policymakers relied on economic models (like input-output models or CGE models) to predict the impact of, say, injecting €100 million of aid into sector X vs. sector Y. AI offers new, more dynamic simulation techniques. By adjusting parameters (e.g. subsidy amounts, eligibility rules) in a simulated environment, AI can help predict how agents would respond – such as how a grant program might affect market competition or regional employment.

Researchers have begun using multi-agent AI models to simulate macroeconomic changes, so that policymakers can evaluate trade-offs of different aid allocations or regulatory choices.

The Case of Romania: Empirical Findings and Challenges

The 2021 World Bank report highlights that although state aid has had a positive impact on economic growth and employment, challenges remain regarding implementation capacity and database fragmentation. For instance, private companies that received aid between 2014 and 2020 reported an average 18% increase in productivity, yet delays in application processing and lack of interoperability between administrative data remain significant barriers.

European Best Practices

Estonia and the Netherlands are relevant examples: both have implemented interconnected digital registries and algorithm-assisted decision-making processes. In Estonia, the X-Road platform enables integration of data from multiple institutions, significantly reducing application processing times. The Netherlands uses a risk scoring system to identify projects requiring detailed audits.

Future Policy Directions and Research Recommendations

a. Develop AI-Ready Regulatory Sandboxes for State Aid:

Governments should implement controlled testing environments where new AI-based tools for state aid management can be safely trialed, evaluated, and scaled. This fosters innovation while ensuring regulatory compliance and risk mitigation.

b. Establish a European Observatory on AI and State Aid:

A dedicated observatory could facilitate the monitoring of AI adoption in state aid across Member States, collect comparative data, and provide policy guidance based on evidence, promoting coherence and mutual learning.

c. Promote Interdisciplinary Research on Ethical AI Governance in Public Policy:

Future academic and policy research should focus on bridging AI technology with legal, ethical, and economic frameworks, ensuring that algorithmic tools align with democratic values and public interest in the design of aid allocation schemes.

Introduction of a clear ethical and legal framework for the use of AI in administrative decisions, in line with the EU AI Act;

Strengthening the digital competencies of staff in managing authorities through continuous training and partnerships with academia and the tech sector.

5. Conclusions

Integrating AI into state aid management is not merely a technological opportunity but a strategic necessity for more efficient, fair, and transparent public governance. For Romania, the success of this transition depends on adapting the legal framework, investing in digital infrastructure, and political commitment to responsible innovation.

Artificial Intelligence not only redefines strategic decision-making at the corporate level but also transforms the state's role in supporting this transition through state aid policies.

Thus, state aid becomes a catalyst for technological progress, supporting the development and adoption of AI-based solutions by enterprises of all sizes. Through well-calibrated support schemes, states can stimulate innovation, bridge technological gaps, and contribute to the sustainable competitiveness of European companies.

Simultaneously, the use of AI in advanced research and predictive analytics enhances corporations' decision-making capabilities, enabling better anticipation of market shifts and

optimization of resource allocation. This synergy between technology and public intervention shapes a new model of economic governance centered on excellence, ethics, and sustainability.

The future of state aid policies in the AI era will depend on the states' ability to combine strategic vision with effective mechanisms for implementation and oversight. Only through such an integrated approach can AI be transformed into a driver of inclusive growth and European prosperity.

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Artificial Intelligence in multinational corporations: catalyst for innovation and strategic alignment

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Abstract. *This article analyzes the transformative impact of Artificial Intelligence (AI) on multinational corporations, with a focus on how AI enhances innovation, strategic alignment, and operational efficiency. The paper explores the role of machine learning and deep learning in automating due diligence, processing vast data sets, and supporting predictive analytics. It highlights AI's ability to uncover hidden patterns, anticipate market changes, and optimize investment decisions. Furthermore, it addresses key challenges related to system integration, data security, and organizational trust. The study concludes that strategically implemented AI technologies can provide multinational companies with a lasting competitive edge in an increasingly volatile and data-driven global economy.*

Keywords: Artificial Intelligence (AI), innovation, competitive advantage, digital transformation.

JEL Classification: M16, L21, O33.

Introduction

In an era marked by accelerated technological transformations, Artificial Intelligence (AI) has become a central pillar in corporate strategies, fundamentally changing the way organizations manage operations, process data, and innovate. This transformation is not just a passing trend but a phenomenon that decisively influences the business models of multinational companies. From automating operational processes to advanced data analysis, AI provides companies with the ability to make more informed, faster, and more efficient decisions.

One of the areas most impacted by this technological revolution is the evaluation process of entities in the context of acquisitions, mergers, or investments. AI optimizes these processes through automation, predictive analysis, and the rapid identification of hidden risks. This article explores how AI influences corporate strategies and its impact on organizational efficiency, with a particular focus on process automation, predictive analysis, and the strategic integration of this technology.

Process Automation: A New Dimension of Efficiency

In the corporate world, every second and every decision matters. The faster a company can evaluate a business opportunity, the more likely it is to maximize its profit and minimize its risks. However, the processes underlying these strategic decisions—such as due diligence—are often time- and resource-consuming, requiring meticulous analysis of vast volumes of financial, legal, and operational data.

Until recently, these analyses were conducted manually by entire teams of specialists who reviewed documents, extracted essential information, and attempted to identify potential risks associated with a transaction. This process not only took weeks or even months but was also prone to human error, which could lead to significant financial losses.

Today, however, AI has begun to fundamentally change this paradigm. With the help of advanced technologies, multinational companies can automate complex processes, accelerating analysis and ensuring superior accuracy. By using machine learning and deep learning algorithms, AI transforms due diligence into a faster, smarter, and more efficient process, freeing expert teams from repetitive tasks and allowing them to focus on interpretation and strategic decision-making.

How Machine Learning Optimizes Data Analysis

At the core of due diligence automation lies the ability of machine learning algorithms to process and analyze massive amounts of data in record time. Unlike traditional methods where analysts had to manually sift through financial reports, contracts, or company histories, AI systems can perform this task in seconds, delivering more accurate and detailed results.

Consider the example of a corporation intending to acquire a smaller company. Before finalizing the transaction, the due diligence team must analyze all aspects of the target business—from its financial status and existing contracts to potential lawsuits or compliance issues. An AI system equipped with machine learning algorithms can

automatically scan and analyze financial reports from the last ten years, identifying any irregularities or anomalies within minutes.

Moreover, these systems do not only identify relevant data but can also detect hidden trends. For example, they may observe a gradual decline in revenue for a company that initially appears stable but is actually facing long-term financial challenges. They can also correlate various datasets to provide a broader perspective on the risks associated with an acquisition.

Another significant advantage of machine learning is its ability to analyze legal documents. Using natural language processing (NLP), AI can quickly extract essential information from contracts, compliance policies, or court rulings. For instance, it can identify problematic clauses in a purchase agreement or flag hidden financial obligations. In doing so, AI not only accelerates the analysis process but also reduces the risk of overlooking critical details.

Deep Learning and Predictive Analysis

While machine learning focuses on analyzing historical data and extracting relevant information, deep learning takes this process to a higher level, allowing companies to anticipate problems before they arise.

A key technology in this regard is the use of complex neural networks that can identify patterns in data and make predictions with remarkable accuracy. For example, a deep learning system can analyze tens of thousands of pages of financial and legal documentation to detect signs of fraud or discrepancies in financial statements.

A concrete case might be sentiment analysis related to a transaction. When a company is on the verge of merging with another, deep learning can analyze tons of publicly available data—from news and press releases to social media discussions—to assess the general perception of the move. If the analysis reveals a negative market sentiment, the company may reconsider the timing of the merger or take additional measures to manage reputational risks.

Deep learning can also be used to evaluate a company's litigation history and determine the likelihood of future legal disputes. For example, if a system detects a pattern of lawsuits filed by former employees, it may be a red flag indicating systemic issues in the organizational culture of that company—an aspect that could influence the acquisition decision.

Furthermore, through these predictive capabilities, AI not only improves the operational efficiency of corporations but also significantly reduces the risks associated with acquisitions and mergers. A company equipped with these technologies can make informed decisions based on a much deeper and more detailed analysis than would be possible using traditional methods.

Advanced Research and Predictive Analysis: A Support for Strategic Decisions

In a dynamic economic environment, where uncertainty and volatility can drastically affect a company's success, strategic decisions can no longer be made solely based on experience

or intuition. AI is fundamentally changing how multinationals conduct research and predictive analysis, providing a perspective grounded in solid data and mathematically precise simulated scenarios.

The use of AI in advanced research not only accelerates data collection and interpretation but also enables companies to identify growth opportunities ahead of competitors, optimize investments, and reduce the risks to which they are exposed. Whether we are talking about economic forecasts, consumer behavior analysis, or anticipating geopolitical events, AI-based systems are becoming indispensable allies in informed decision-making.

Anticipating Market Changes

One of the most powerful applications of AI in the business environment is its ability to anticipate market shifts. Machine learning algorithms can analyze vast volumes of historical data, identifying patterns and trends that might escape human analysis.

For example, a company in the real estate sector can use AI to analyze property price histories, demand in different regions, and external factors such as interest rates or government policies, thus generating accurate forecasts of market evolution. This allows real estate developers to make more informed decisions regarding land acquisitions and the optimal timing for selling or renting properties.

Similarly, in the financial sector, advanced algorithms can analyze millions of stock market transactions to predict market volatility. An AI system can detect behavioral patterns in stock activity, correlate them with economic or geopolitical events, and provide more precise investment recommendations than traditional methods.

Optimizing the Investment Portfolio

An investment decision involves carefully balancing potential returns with assumed risks. AI has become an essential tool for companies seeking to maximize their return on investment by simultaneously analyzing hundreds of economic and financial variables to construct the most realistic market scenarios.

Take, for example, an investment fund aiming to diversify its portfolio. Instead of relying solely on the expertise of human analysts, it can use machine learning algorithms that analyze past performance of various assets, economic trends, and macroeconomic factors, generating recommendations based on precise probabilities.

Moreover, AI systems not only analyze existing data but also continuously learn from it, constantly improving their predictive models. For instance, they can detect unexpected correlations between oil prices and the performance of certain industries, offering investors a new perspective on market risks and opportunities.

Additionally, in the banking industry, AI can be used to optimize loan portfolios, identifying low-risk borrowers and establishing personalized interest rates based on each client's financial profile. This way, banks can reduce the rate of non-performing loans and increase the profitability of their operations.

Risk Management

In a globalized economic landscape, the risks faced by large companies are becoming increasingly complex and unpredictable. Whether we speak of economic crises, geopolitical instability, or fluctuations in financial markets, the ability to anticipate and manage these risks can make the difference between success and failure.

AI offers a revolutionary approach in this domain, allowing for the simultaneous evaluation of numerous risk scenarios and providing decision-makers with real-time information to take the necessary measures.

A relevant example is the analysis of the impact of global economic fluctuations on a multinational. An AI system can analyze historical data from previous economic crises, identifying indicators that preceded recessions. Based on this information, it can generate predictive models on the likelihood of future economic difficulties and suggest strategies to minimize the impact on the company.

AI can also evaluate geopolitical risks. For instance, a corporation operating internationally can use AI to analyze data related to political instability in a specific region, assessing its impact on the supply chain. If an algorithm detects a high risk of conflict or economic sanctions, the company can decide to relocate production to another country before the situation escalates.

Moreover, in the insurance sector, AI is used to assess fraud risk and detect suspicious patterns in claims. By analyzing transaction history and customer behavior, AI systems can automatically flag claims that present a high risk of fraud, thereby reducing financial losses for insurance companies.

Challenges and Perspectives: The Strategic Integration of AI

Although AI offers multiple benefits to companies, its large-scale implementation is not without challenges. Effectively integrating AI into business strategies requires not only advanced technology but also a profound adaptation of organizational processes, corporate culture, and IT infrastructure.

Any company that wants to adopt AI must carefully analyze its needs, resources, and adaptability to avoid roadblocks and maximize the positive impact of new technologies. Among the main challenges are:

1. Integration with Existing Systems

One of the biggest difficulties is integrating AI-based solutions with a company's existing IT infrastructure. Many multinationals operate with outdated systems, sometimes based on legacy technologies that are not compatible with new machine learning and predictive analytics platforms.

The integration process involves not only updating hardware and software but also ensuring effective interoperability between AI systems and the company's existing databases. For example, a company implementing an AI-based analytics system must ensure that it can

extract, process, and interpret data stored in its current infrastructure without causing delays or operational errors.

To overcome this challenge, many organizations choose a phased approach, implementing AI in pilot departments, testing compatibility with existing systems, and gradually adjusting processes.

2. Data Security and Transparency

Another critical aspect of adopting AI is protecting and safeguarding data privacy. AI systems rely on access to large volumes of information to learn and make decisions, which makes them vulnerable to cyberattacks, data leaks, or misuse of sensitive information.

Without solid security measures, companies may face major risks, including data theft, information manipulation, or loss of customer trust. For example, an AI algorithm used for financial analysis must access critical information about the company and its clients. If this data is not well protected, it could become the target of cyberattacks.

To minimize these risks, companies must implement strict data security policies, including data encryption, multi-factor authentication, and regular audits of AI systems. Additionally, ensuring transparency in AI decision-making processes is essential so that users understand how data is analyzed and how recommendations are generated.

3. Building and Maintaining Trust in Automated Decisions

Even though AI can provide precise predictions and complex analyses, the human factor remains essential in making strategic decisions. Many organizations face employee and executive reluctance to fully trust automated recommendations.

This lack of trust may be driven by several factors: the opacity of algorithms, the fear that AI could replace jobs, or concerns about errors that could affect a company's financial results.

To counter these fears, companies must adopt a clear AI integration strategy, based on:

- **Algorithm explainability** – Developing AI models that provide clear explanations for the decisions they make, so users can understand the logic behind them.
- **Employee involvement** – Training teams to use AI and integrating the technology as a complementary tool, not a replacement for human work.
- **Continuous testing and validation** – Using diverse datasets to constantly test algorithms, ensuring that they produce fair and accurate results.

Future Perspectives

To overcome these challenges, companies must invest not only in technology but also in people and processes. Developing digital skills among teams, modernizing IT infrastructure, and adopting an open mindset toward change are essential steps for the successful integration of AI.

In the future, AI technologies are expected to become increasingly accessible and easier to implement. At the same time, regulations regarding the use of AI will continue to evolve, emphasizing ethics, security, and data protection. Companies that manage to combine technological innovation with a clear integration strategy will gain a significant competitive advantage, strengthening their market position and optimizing operational performance.

AI is not just a passing trend, but a revolution that is transforming how organizations make decisions, analyze data, and develop their strategies. With carefully planned implementation and a long-term vision, companies can turn challenges into opportunities and fully harness the potential of AI in the digital age.

Conclusion

The automation of processes through AI has become a major competitive advantage for multinational companies. By using machine learning and deep learning, due diligence has evolved into a faster, more accurate, and more efficient process, allowing corporations to reduce their risk exposure and make better-informed strategic decisions.

In a dynamic business environment where every second counts, the ability to quickly analyze data and anticipate future problems can make the difference between success and failure. Therefore, companies that adopt and integrate AI into their operational processes not only optimize efficiency but also secure a lasting competitive edge in the global economy.

Advanced research and predictive analysis powered by AI are quickly becoming essential pillars of modern business strategies. The ability to anticipate market changes, optimize investments, and proactively manage risks gives large corporations a crucial competitive advantage.

In a world where information is power, AI not only accelerates the decision-making process but also makes it significantly more precise. With the help of these technologies, companies are no longer just spectators of economic changes—they become key actors shaping the future of the market and securing a leading position in the global economy.

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Artificial Intelligence and the economy of the future: between potential and responsibility

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Abstract. *This paper explores the impact of artificial intelligence (AI) on the future economy, highlighting its potential to accelerate productivity, stimulate innovation, and support sustainable economic development. Amid rapid technological advances, AI is reshaping business models, value chains, and the skills required in the labor market. The study is based on a literature review, complemented by practical examples from the economy and industry. It also discusses the challenges associated with AI use, such as digital inequality, ethical risks, and the need for responsible public policies. The conclusions emphasize the need for a balance between innovation and regulation, with a focus on education and inter-institutional collaboration to harness the benefits of artificial intelligence.*

Keywords: Artificial Intelligence (AI), innovation, productivity, technological change, public policy, education and skills.

JEL Classification: J24, O33, O34.

1. Introduction

In the context of a constantly evolving global economy, artificial intelligence (AI) has become one of the main drivers of change. Advances in fields such as machine learning, natural language processing, and predictive analytics have enabled AI to be applied across multiple economic sectors, from industry and healthcare to education and financial services. At the same time, AI raises essential questions about sustainability, equity, and the social responsibility of economic transformations.

The purpose of this paper is to analyze how AI contributes to reshaping the economic landscape, identifying both the opportunities offered by this technology and the associated ethical, social, and political challenges. The research aims to provide a balanced perspective on the relationship between technological progress and sustainable development, with a focus on how AI can be used for the benefit of the economy and society. The paper is based on current specialized literature, supplemented by relevant reports and examples, and aims to contribute to the academic debate on the responsible integration of AI into contemporary economic dynamics.

2. State of Knowledge

In the specialized literature, artificial intelligence is approached from multiple perspectives, from technical and applied aspects to macroeconomic implications. Studies by PwC (2017) highlight that AI has the potential to contribute up to 14% to global GDP by 2030, equivalent to \$15.7 trillion, through productivity growth and the emergence of improved products and services. The McKinsey Global Institute (2018) estimates that large-scale AI adoption could add \$13 trillion to the global economy by 2030, which would represent an average annual global GDP growth of 1.2%, offering a significant competitive advantage through automation and decision optimization.

Academic researchers such as Brynjolfsson & McAfee (2017) and Agrawal et al. (2018) argue that AI may play a role similar to electricity during the industrial revolution, due to its ability to expand the boundaries of decision-making and innovation. At the same time, literature highlights concerns about the distribution of AI benefits, the impact on jobs, and rising social inequalities (Acemoglu & Restrepo, 2020).

At the European Union level, strategic documents such as the "Coordinated Plan on Artificial Intelligence" (2021) promote a balanced approach between innovation and regulation, emphasizing trustworthy AI that respects fundamental values and rights (European Commission, 2021).

Although the literature is rich in analyses regarding the technological potential and economic impact of AI, there is a significant gap in addressing the integrated economic, social, and ethical responsibility in the adoption of these technologies. This paper aims to address this gap by combining the economic perspective with that of sustainable development and social equity, providing an analytical framework for the responsible understanding of AI's role in the economy of the future.

3. Research Methodology

This paper uses a documentary and comparative analysis approach based on relevant secondary sources from academic literature, international reports, and strategic documents. Sources were selected based on their currency (from the past 5–7 years), relevance to the topic, and editorial credibility (indexed journals, institutional publications, international organizations).

The documentary analysis included reports from OECD (2021, 2023), McKinsey Global Institute (2021), as well as academic research by authors such as Brynjolfsson & McAfee (2017), Acemoglu & Restrepo (2020), and Agrawal et al. (2018). These sources were examined to identify key trends, risks, and opportunities generated by AI adoption in the economy.

The comparative method was used to analyze different AI integration models in the economy, with a focus on the distinction between developed and developing countries, as well as the varied impact by economic sector (industry, services, public administration).

To complement the classic theoretical analysis, the author also included an exploratory qualitative component in the form of a structured dialogue with an advanced language model – ChatGPT. This discussion aimed to formulate hypotheses, conduct a conceptual analysis of the literature, and validate the logic of the presented arguments. The conversation served as a critical and reflective support for structuring ideas and outlining economic and ethical perspectives on AI.

Research Objectives:

- Identify the main economic benefits associated with AI adoption;
- Highlight systemic and social risks generated by AI;
- Propose an analytical framework that allows responsible AI integration into the future economy.

The research is exploratory and analytical in nature, aiming to provide a solid foundation for future academic reflections and developments in the field of technology-augmented economics.

4. Results and Discussion

This section integrates both the results obtained from the analysis of the literature and specialized sources, as well as representative elements from the exploratory dialogue conducted by the author with ChatGPT, in its role as an argumentative interlocutor. The dialogue was focused on clarifying the economic impact of AI, evaluating ethical risks, and identifying strategic directions for the sustainable integration of these technologies.

4.1. AI and Productivity Growth

The adoption of artificial intelligence in the economy has a significant impact on productivity, especially through the automation of repetitive processes, real-time data analysis, and the optimization of supply chains. According to a McKinsey Global Institute

report (2021), AI can increase labor productivity by up to 40% in certain sectors, such as manufacturing, logistics, and financial services. Implementing technologies like machine learning and robotic process automation (RPA) reduces errors and improves execution times, leading to significant cost savings and increased operational efficiency. Additionally, AI enables better resource allocation and finer control over economic processes, thus enhancing global competitiveness for businesses.

4.2. AI and Economic Innovation

Artificial intelligence not only optimizes existing processes but also facilitates the emergence of innovative business models. Notable examples include AI-based services in fields such as healthcare (algorithm-assisted diagnosis), agriculture (drone monitoring and predictive analysis), or personalized education. According to Agrawal et al. (2018), AI can reduce the costs of experimentation and testing, thereby accelerating the pace of innovation. Moreover, companies that adopt AI are better prepared to enter new markets and respond quickly to changes in the business environment. AI also allows for better customization of products and services by analyzing consumer preferences, leading to increased added value in the economy.

4.3. Economic and Social Responsibility in the AI Era

As AI becomes increasingly integrated into the economy, concerns arise regarding equity, transparency, and its impact on employment. Acemoglu & Restrepo (2020) warn that AI could exacerbate labor market polarization by eliminating middle-skill jobs and increasing social inequalities. Additionally, the use of AI in automated decision-making raises questions about algorithmic bias and institutional accountability. Organizations such as the OECD (2021) and the European Commission emphasize the need for a legislative framework that ensures human rights, data protection, and traceability of decisions made by autonomous systems. Public policies must also support professional retraining and digital inclusion to prevent the socio-economic exclusion of vulnerable groups.

4.4. Dialogue: Author – AI Instrument

Author: What economic aspects are most influenced by artificial intelligence today?

ChatGPT: Currently, AI significantly influences areas such as labor productivity, cost optimization, and innovation. In industry, AI reduces errors and processing time. In the services sector, it enables personalized offers and automates customer interactions.

Author: What is the main risk associated with integrating AI into the economy?

ChatGPT: One of the most significant risks is labor market polarization. AI tends to replace routine tasks, especially affecting middle-skill jobs. There are also concerns about algorithmic bias and the lack of transparency in automated decision-making processes.

Author: Can AI contribute to a more sustainable economy?

ChatGPT: Yes, AI can promote sustainability by optimizing resource use, reducing waste, and improving logistics. In agriculture, for example, AI can help manage water and fertilizers. However, these benefits must be weighed against the energy consumption of AI systems.

Author: What role do public policies play in ensuring ethical and responsible use of AI?

ChatGPT: Public policies must establish clear guidelines for ethical AI use, invest in digital education, and encourage collaboration between academia, industry, and the public sector. Mechanisms for AI auditing and control should also be developed.

Author: What ethical responsibilities should we assume regarding equity and the academic use of AI?

ChatGPT: Responsible AI use involves ensuring equitable access to these technologies so that their benefits are not concentrated in the hands of a few economic actors. In academia, AI must be used transparently, with clear disclosure of algorithmic contributions, to prevent intellectual fraud and maintain research integrity. AI education must also be accessible to disadvantaged groups to reduce the digital divide.

4.5. Synthesis and Perspective

The analysis results show that AI is a tool with enormous transformational potential for the economy, provided its adoption is accompanied by coherent public policies, investments in digital education, and a solid ethical framework. Effective AI integration requires a systemic vision that combines technological innovation with social responsibility so that economic benefits are distributed fairly and risks are properly managed. A collaborative approach among academia, the private sector, and public authorities is essential to create a sustainable digital ecosystem based on trust, transparency, and shared progress.

5. Conclusions

The analysis, enriched by reflections generated through the interactive discussion between the author and ChatGPT, highlights that artificial intelligence is one of the most influential emerging technologies capable of profoundly reshaping the global economic architecture. Its impact is manifested in productivity growth, accelerated innovation, and business model transformation, but it also brings substantial challenges, such as labor market polarization, risks related to non-transparent data use, and deepening socio-economic inequalities.

To harness AI's potential in a balanced and sustainable way, economic and educational strategies should include the following recommendations:

- Develop proactive public policies that promote responsible, transparent, and explainable AI through a flexible and adaptive legislative framework;
- Make sustained investments in digital education, both in pre-university and university education, as well as through lifelong learning and professional retraining programs for the current workforce;
- Support interdisciplinary research and innovation by funding projects that connect technology, economics, and social sciences to develop equitable and sustainable solutions;
- Promote digital inclusion by ensuring equal access to digital infrastructure and reducing technological gaps between regions and social groups;

- Create strategic partnerships among the public sector, academia, and private industry to generate a collaborative and responsible innovation ecosystem.

Ultimately, AI should not be viewed solely as a disruptive technology, but as an economic and social infrastructure that requires an integrated vision, a solid ethical foundation, and smart governance. Only through a balanced and forward-looking approach can AI contribute to a more efficient, equitable, and humane economy.

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Investigating the main challenges AI integration into higher education settings

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Abstract. *This study investigates the main challenges of incorporating Artificial Intelligence (AI) into Higher Education landscape through a systematic literature review. Additionally, this research contributes to ongoing discussions on AI's role in higher education with the purpose of offering practical recommendations to ensure that AI enhances learning and administrative processes rather than creating additional challenges. Thus, our research identifies key issues related to adopting AI-driven tools in academia, such as data privacy, ethical concerns, faculty resistance, and technological accessibility. These findings provide universities valuable insights mandatory to be adopted for responsible AI implementation while also balancing innovation and ethical considerations.*

Keywords: higher education, Artificial Intelligence, AI in education (AIED), academia, systematic literature review.

JEL Classification: I23, O33, D83, L86, Q55.

1. Introduction

The integration of Artificial Intelligence (AI) into higher education settings has emerged as a topic of growing significance especially after the OpenAI launched in 2022 their free generative AI model, ChatGPT. Recent years have witnessed an exponential rise in research focused on integrating AI tools to enhance educational outcomes, personalisation, assessment, and institutional management (Bond et al., 2024; Marengo et al., 2024). Yet, while the potential beneficial advantages are widely acknowledged, there still remain concerns with regards to ethical issues, data privacy, equity, and human oversight (Zawacki-Richter et al., 2019; Bozkurt et al., 2020). Thus, addressing these challenges becomes critical to guarantee that AI serves as a facilitator of educational advancements rather than an additional source of complexity.

Previous literature reviews have provided valuable insights into the current trends, applications, and ethical considerations of AI integration in higher education (Wang et al., 2024; Safiulina et al., 2024). In particular, Le Dinh et al. (2025) propose the Human-Centred AI for Systematic Literature Reviews (HCAI-SLR) framework, particularly relevant as it puts an emphasis on the need to maintain a balance between technological innovation and critical human oversight. This conceptual framework integrates AI-driven processes with human judgment and ethical checkpoints throughout the entire research process. In contrast, divergent perspectives place an emphasis on AI's unintended negative effects concerning inclusion, faculty resistance, and technological accessibility (Suazo Galdames, 2024).

In spite of the richness of the existing research, a critical gap remains as the specific challenges associated with the adoption and responsible integration of AI into higher education settings have not been comprehensively synthesised in a way that provides actionable recommendations for institutions. Previous works have either broadly focused on applications or ethical aspects but an in-depth challenge-oriented analysis remains underdeveloped.

Hence, the present study aims to fill this gap by systematically reviewing the main challenges of incorporating AI into higher education settings, guided by the HCAI-SLR framework. The main objective is to provide a classification of key barriers, such as data privacy issues, ethical dilemmas, faculty resistance, and technological inequities, and propose practical recommendations that universities can adopt to ensure responsible human-centred AI integration. Consequently, this research contributes to ongoing discussions about the role of AI in academia and aims to provide institutions with strategic insights necessary for balancing innovation with ethical responsibility.

The remainder of this paper continues with the rigorous analysis of the most relevant literature in this field of knowledge, followed by the clarification and justification of the methodology adopted for the systematic literature review. Next, the results section carries out an analysis of the main challenges identified with regards to AI integration in higher education, while the discussion part provides a description of practical implications and

makes an attempt to give further recommendations for institutions. Finally, the last section of this paper concludes the study and gives a short overview of the principal findings while also indicating further research directions.

2. Literature review

The integration of Artificial Intelligence (AI) into Higher Education institutions (HEI) has become an increasingly important research domain driven by the fast pace of the technological change AI-centred via numerous tools equipped with the potential to virtually transform the entire educational ecosystem through revolutionising teaching, learning, and institutional processes. Yet, the current body of scientific literature provides a description of a very complex landscape marked by significant gaps in terms of AI tools aligned with educational objectives, as well as ethical and responsible AI implementation. Thus, this literature review makes an attempt to address these gaps by drawing on studies that place emphasis on the need for further research in AI's role in HE, but also carries out an exploration of these studies' impact on the field of knowledge, and conducts an investigation on key theoretical frameworks that inform the research direction of this study.

On the one hand, several key studies put emphasis on the necessity of addressing the integration of AI in HE mainly due to issues related to ethical concerns and lack of educational strategies AI-based. For instance, the work of Aler Tubella et al. (2024) places emphasis on the challenges generated by the effort of translating the European Union's Ethics Guidelines for Trustworthy AI into educational practices, or asserting the inconsistency across institutions of policy application within the curriculum. In addition, the authors argue that educators need to incorporate specific AI methodologies in their teaching to guarantee individual understanding and engagement with AI under ethical principles for each student, but also to prepare them for an AI-centred future (Aler Tubella et al., 2024). Their conclusion resonates with Manzano and González (2024) who suggest that AI's integration into HE demands for specific skills, such as critical knowledge with regards to ethics and responsibility, while they also place emphasis on the need for students to develop a "human on the loop" mentality to ensure that AI applications adhere to ethical standards aligned with the United Nations' Sustainable Development Goals (SDGs) and Universal Design for Learning (UDL).

Similarly, the work of Reiter et al. (2025) carries out an exploration of the increasing prevalence of AI tools among students, particularly for solving academic tasks, while they also provide a classification of the significant risks of misuse where cheating leads the hierarchy. Students' preference for multiple AI tools seems to be grounded on these instruments' ability to personalise learning and provide additional explanations of theoretical material, making ethical implementation of AI technologies a key issue in light of the scope that they complement rather than supplant traditional pedagogical methods (Chen et al., 2020; Zeleneva et al., 2025). Another teacher-oriented challenge is defined by the difficulty in distinguishing between AI-generated content and student-generated work, with direct effect on reduced academic integrity (Kasneci et al., 2023). Thus, the authors

make an attempt to inform stakeholders on the growing need to balance AI adoption with responsible use, mainly grounded on their findings which suggest that AI integration in HE requires both technical and ethical expertise if the objective is to avoid misuse (Zawachi-Richter et al., 2019; Zeleneva et al., 2025).

On the other hand, this research draws on several key theoretical frameworks and prior studies that have shaped its approach. In line with the conclusions of Popenici and Kerr (2017) that argue for thoughtful AI incorporation into educational settings centred on humanistic and pedagogical values, the work of Aler Tubella et al. (2024) is foundational in shaping the study's focus on trustworthy AI and its implications for higher education curricula, due to their recommendation to properly integrate AI into educational settings firstly by explicitly stating the skills and competencies students need. Thus, this aligns with the study's objective of formulating recommendations for educators to integrate AI responsibly into teaching practices. Moreover, the studies by Temper et al. (2025) and Sposato (2025) provide important theoretical contributions. The work of Temper et al. (2025) advocates for the use of risk-based regulatory frameworks like the EU's AI Act to guide AI implementation in educational settings as a structured and responsible process. Meanwhile, the study of Sposato (2025) provides a comprehensive taxonomy of AI applications in HE leadership, serving as a useful model for organising AI-related activities within educational institutions that range from administrative efficiency to personalised learning.

Furthermore, several previous studies point out that resource disparities and institutional readiness are two interconnected factors with significant impact on successful integration of AI in higher education. Due to the fact that institutions with limited resources face numerous challenges such as negative effect on student learning or faculty competitiveness (Chen et al., 2020), scholars put emphasis on the uneven distribution of AI resources and the resulting global inequalities in higher education (Aktürk, 2024; Zhan et al., 2024).

Unlike prior research studies that often isolate specific issues, this paper comprehensively maps the interconnected challenges associated with AI integration into HEI landscape, from the lack of theoretical grounding and faculty training programs to ethical dilemmas and resource disparities. Hence, the novelty of this article lies in the multidimensional framework it provides centred on pedagogical, ethical, institutional, and practical perspectives on AI adoption in academia.

3. Methodology

This research paper aims to conduct a thorough analysis of the barriers and challenges associated with the integration of artificial intelligence (AI) into HEI. Respectively, this article makes an attempt to bring together perspectives from recent peer-reviewed literature to construct a comprehensive and multidimensional understanding of the topic. Thus, a systematic literature review was conducted due to the fact that this method is widely accepted for synthesising existing research to reveal thematic trends and theoretical gaps.

This method's appropriateness is justified by the conceptual and exploratory nature of the study focused on the examination of theoretical debates and emerging empirical findings.

Since it provides clear guidance on transparent and rigorous selection of sources, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework was applied for the methodological approach. With focus on articles that addressed AI integration in higher education and reported either conceptual insights or empirical data, a purposive sampling strategy was implemented. The selected documents were retrieved from Scopus database, using the following search query: "artificial intelligence" and/or "higher education" and/or "barriers" and/or "challenges" and/or "ethics" and/or "AI adoption". These articles were published between 2017 and 2025 and were selected for their thematic convergence with our research endeavour.

In the first stage, two hundred twenty-seven academic articles were included in the sample. Upon applying exclusion criteria, thirty-four research papers were selected in the final sample because they clearly examined the intersection between AI technologies and educational systems. The review took into consideration only publicly available and peer-reviewed articles, while the formal analysis is entirely based on secondary data from published sources. In addition, the analytical process was conducted using narrative synthesis, which is a qualitative method that allows the researcher to identify themes and draw out connections across studies that use different methodologies. Through this process, the selected literature was systematically coded for recurring patterns, revealing five core themes: (1) lack of faculty preparedness and training; (2) ethical uncertainty surrounding AI implementation; (3) institutional resistance to change; (4) digital infrastructure gaps; and (5) conceptual ambiguity in defining AI's role in pedagogy.

In spite of its rigorous methodological approach, this paper has several limitations. The first limit refers to the overreliance on English-language publications, while other relevant studies published in other languages might have been omitted. Furthermore, as a conceptual review, this research paper presents findings impossible to be generalised statistically.

4. Results and discussions

4.1. Data privacy concerns

One of the most frequently discussed challenges in the reviewed literature concerns the issue of data privacy and the ethical handling of student information. Moreover, Francis et al. (2024) put emphasis on the fact that the use of generative AI tools in higher education environments raises questions about how sensitive academic data, such as student performance and identity, is collected, stored, and processed. In addition, their work places emphasis on the potential for unauthorised access and misuse if robust institutional safeguards are not implemented. Likewise, Demir and Demir (2024) suggest that academia face struggle in balancing the benefits of AI-powered personalisation with the risks associated with data surveillance. For this reason, they suggest adopting clear frameworks for transparent data governance, as well as student consent protocols in AI integration strategies.

4.2. Algorithmic bias

Algorithmic bias emerged as a critical concern across multiple recent studies, with George and Wooden (2023) indicating that AI systems deployed in higher education often lack contextual sensitivity and lead to unequal outcomes, particularly in academic assessments and admissions processes. Similarly, the work of Gallent-Torres et al. (2024) further warn that algorithmic decision-making can unintentionally reinforce pre-existing societal inequalities if training data is not adequately diversified, whilst Samman (2024) demonstrates that discrepancies in AI outputs may stem from regional, linguistic, or cultural misrepresentations embedded in AI models. Their concern is echoed by the conclusion of Doğan et al. (2025) who indicate that faculty members express scepticism about the objectivity of AI-based recommendations. Furthermore, the research by Mahmud et al. (2025) confirms that academic staff are apprehensive about the opacity of algorithmic logic, whereas Lünich et al. (2024) show that students and the general public differ significantly in their risk perception related to predictive analytics. For this purpose, scholars recommend ethical audits and regulatory oversight as necessary steps to minimise bias in AI applications (Abulibdeh et al., 2025).

4.3. Educational inequality

The potential for AI to both bridge and widen educational inequality was frequently discussed in the scientific literature. Despite the fact that the research by Gallent-Torres et al. (2024) place emphasis on the potential of AI-driven tools to support inclusivity through adaptive learning, it also suggests that integrating AI into higher education settings can exacerbate digital divides because access to technology is rather uneven across regions. In fact, scholars speculate that without institutional safeguards, AI tools might advantage students who are already more digitally literate (Francis et al., 2024). In a similar study related to the AI-driven digital gap, Doğan et al. (2025) point out that institutions in less developed regions face greater challenges in AI adoption due to limited infrastructure and funding. Moreover, the work of Demir and Demir (2024) contend that a one-size-fits-all approach in AI implementation could further disadvantage non-traditional learners and students from underrepresented backgrounds, thus increasing the digital divide if further stratification in higher education is not prevented through equity-oriented AI deployment strategies and methodologies.

4.4. Job displacement

In the post-pandemic era when the transition to Industry 5.0 has been catalysed by the expansion of innovative AI-driven technologies widely adopted by individuals from higher education environments mainly because students were the first adopters of generative language models, scholars also warn about job displacement due to AI integration across industries. Recent studies report that many educators fear automation could lead to reduced demand for academic and administrative staff (Doğan et al., 2025), or even anxiety issues among faculty members over being replaced or devaluated by AI teaching assistants and content generators like ChatGPT (Gammoh, 2025). In a similar note, George and Wooden (2023) intimate that while AI can streamline institutional operations, it may also result in

strategic downsizing of the human workforce. This perspective is reinforced by Kilianova et al. (2025) who suggest that while AI can enhance teaching efficiency, it often leads to restructuring and role redefinition among educators. However, despite these concerns, the literature also acknowledges opportunities for professional reskilling and role transformation with a shift toward more supervisory and creative educational tasks.

4.5. Reduced human interaction

A dominant theme that emerged across studies was the significant reduction in human interaction in academic settings, attributed largely to the increasing integration of generative AI tools. Studies show that students have become increasingly reliant on digital solutions such as ChatGPT and other large language models, not merely as supplementary resources, but as primary means of generating assignments, drafting essays, and even preparing for oral assessments (Doğan et al., 2025). This trend was perceived to compromise the pedagogical value of student-teacher engagement, reducing the frequency and depth of interpersonal dialogue that traditionally places emphasis on effective academic mentorship and formative feedback. These trends are echoed in Abulibdeh et al. (2025), who provide a strategic overview of AI's role in institutional development through a scoping review where they draw attention to the unintended consequences of automation in learning processes, and note that while administrative and content delivery functions benefit from AI augmentation, students risk to become passive recipients rather than active constructors of knowledge. Moreover, the overuse of AI for convenience and speed fosters transactional learning models that favour outcome over process and undermine the social and communicative competencies that face-to-face settings cultivate.

4.6. Academic integrity

One of the most widely cited concerns in the literature is the impact of AI on academic integrity. Mahmud et al. (2025) observe that university faculty staff faces real struggle to differentiate between authentic and AI-generated work, which leads to a growing distrust in assessment outcomes. Despite the pedagogical advantages that generative AI tools offer, they simultaneously blur the line between original thinking and algorithmically generated content, thus challenging traditional notions of authorship and learning (Francis et al., 2024). Additionally, Gammoh (2025) supports the view that educators report increased pressure to revise academic integrity policies, while Vieriu and Petrea (2025) put emphasis on the risk of students becoming overly reliant on AI-generated content, while reducing their critical thinking and originality.

4.7. Accuracy and reliability

Furthermore, concerns over the accuracy and reliability of AI tools persist across multiple educational contexts. For example, the work of Karan and Angadi (2023) warns of hallucinations in large language models and potential inaccuracies when AI systems are used without human oversight, while the research by Aladi (2024) connects trust in AI systems with faculty members' prior exposure to technological change, thus arguing that low trust correlates with low adoption rates. Meanwhile, Symeou et al. (2025) recommend

the implementation of multidisciplinary evidence-based protocols to vet AI-generated content, thereby improving reliability and safeguarding student outcomes.

4.8. Ethical concerns

As AI tools, particularly generative AI models like ChatGPT, become more widespread in educational settings, ethical challenges related to data privacy, consent, transparency, accountability, and equity have grown increasingly complex. One of the core concerns relates to academic integrity, where AI tools might facilitate dishonest academic practices such as plagiarism or unauthorised assistance in assessments. Studies emphasise the dual nature of AI in education because, while it offers innovative potential for pedagogy and content delivery, it also risks being misused in ways that compromise academic standards and devalue genuine learning efforts (Gallent-Torres et al., 2024; Sposato, 2025).

Moreover, the opacity of AI algorithms, particularly in generative models, raises important issues of transparency. Thus, students and educators often interact with AI tools without fully understanding how data is processed or how decisions are generated. Samman (2024) discusses this in a meta-analysis and recommends more rigorous ethical oversight in AI tool implementation, while he also calls attention to how students' data are collected and utilised without explicit informed consent in many cases. Similarly, Francis et al. (2024) further stress the ethical balancing act that institutions must maintain when integrating AI tools because ethical integrity is non-negotiable even if the main objective is achieving innovation. Additionally, Kilianova et al. (2025) assert that the lack of digital literacy and ethical training among both students and educators amplifies the risks. The lack of digital literacy translates into users unintentionally relying on biased outputs or inadvertently sharing sensitive data because of not possessing proper understanding, which further leads to ethical breaches. Consequently, their research recommends the inclusion of digital ethics and AI literacy in university curricula to cultivate a more responsible academic environment.

Furthermore, trust is another ethical component addressed by the study by Aladi (2024), who found that higher education teachers show varied levels of trust in AI-enabled educational technologies. This study places emphasis on the fact that ethical adoption depends not only on the technology itself but also on users' perception of fairness, legitimacy, and control. Hence, if educators and students perceive AI as having negative effects on their autonomy or as an intrusive tool, resistance to adoption may grow, potentially stalling innovation. To address the ethical challenges of AI in education, the study by Symeou et al. (2025) proposes the development of evidence-based guidelines through interdisciplinary collaboration and places emphasis on the importance of stakeholder involvement notably that of educators, developers, and policymakers, in co-creating ethical standards that can be adapted across institutional contexts.

4.9. Increased workload

One significant unintended consequence of AI adoption in higher education, particularly for academic staff, seems to be the increased workload because these instruments' integration often demands new skills, continuous adaptation, and additional responsibilities

for educators, despite their promise for augmented efficiency. In a study focused on university educators in Jordan, researchers found that instructors frequently experience increased cognitive and administrative burdens due to the need to supervise, evaluate, and regulate the use of AI tools among students (Gammoh, 2025). This also includes redesigning curricula, updating assessment criteria, and monitoring for AI-assisted misconduct, all of which can add to educators' already demanding workloads.

Moreover, instructors are expected to remain updated with evolving AI technologies, a task that is often time-consuming and lacks institutional support, mainly because universities have not yet implemented structured training programs, hereby leaving educators to rely on self-learning or peer networks. This scenario may lead to professional burnout or disengagement among older faculty members less accustomed to rapid technological shifts (Gammoh, 2025). Additionally, the deployment of AI systems for tasks such as plagiarism detection or grading may require manual verification, as educators often distrust fully automated outcomes. Consequently, instead of reducing workload, AI can inadvertently duplicate tasks or increase time spent ensuring accuracy and fairness.

4.10. Digital divide

The implementation of generative AI in higher education raises serious concerns about the digital divide, particularly in terms of equitable access to digital resources, infrastructure, and literacy. Even though AI tools like ChatGPT offer novel learning opportunities, their benefits are not evenly distributed and students from underserved or rural backgrounds may lack access to high-speed internet, up-to-date devices, or AI-powered learning platforms, resulting in unequal learning conditions (Francis et al., 2024). Moreover, digital literacy is now a prerequisite for academic participation, notably as AI becomes embedded in assignment creation, exam preparation, and research assistance, which is why possessing digital skills could enhance the utility of AI in educational settings (Demir and Demir, 2024). However, faculty members from marginalised regions may lack the institutional or financial support required to experiment with or implement AI in their classrooms. For this purpose, AI integration must be guided by a commitment to inclusion and should include dedicated policies for accessibility, training, and infrastructural upgrades (Francis et al., 2024).

Nonetheless, the digital divide also manifests in language and cultural biases embedded in generative AI models. Hence, students whose native language or cultural context diverges from dominant English-language datasets may find outputs irrelevant, inaccessible, or even discriminatory.

4.11. Autonomy and control

The increased integration of AI in higher education poses a challenge to traditional notions of autonomy and control, especially in decision-making processes related to teaching, learning, and academic evaluation. The paper of Lünich et al. (2024) explores these tensions in the context of academic performance prediction systems in Germany, finding diverging perceptions between students and the public regarding AI's role in education. For example, while some view AI as a supportive assistant, others express concern about

over-reliance on algorithmic recommendations that might bypass human judgment. They also point out to the potential for AI systems to disempower educators and students and shift control away from individuals toward opaque technological processes. Other scholars put emphasis on the dangers of automated educational governance, where decision-making increasingly depends on data-driven tools (Karan and Angadi, 2023). Such practices can entrench systemic biases and reduce opportunities for personalised learning, because students might become passive recipients of knowledge and lose critical thinking skills and intellectual independence whenever using AI-tools for generating content.

Consequently, to protect academic autonomy in the age of AI universities must adopt technical safeguards and strong ethical and pedagogical commitments that promote transparency, explainability, and user control for the purpose of fostering environments where AI tools are used as collaborative aids rather than authoritative substitutes.

4.12. Functional risks

Functional risks include algorithmic errors, inadequate contextual understanding, and misalignment with pedagogical goals, which arise from the practical limitations and design flaws of artificial intelligence systems used in education. In spite of the integration of AI tools with the intent to enhance efficiency and personalise learning experiences, they often operate with significant technical imperfections (Karan and Angadi, 2023). For instance, educational AI systems may misinterpret student input due to linguistic nuances, cultural variations, or domain-specific terminology, thus leading to inaccurate feedback or flawed assessments. Additionally, such functional errors risk eroding student trust in the learning process and may produce counterproductive outcomes if not closely monitored by educators.

Another concern related to functional risks AI-driven is the lack of adaptability of AI tools to complex, dynamic classroom settings. Unlike human instructors, these systems cannot always recognise emotional cues, respond to spontaneous questions, or accommodate students with diverse learning needs. Moreover, they can generate confusion, reinforce misconceptions, or hinder the learning process rather than support it whenever they fail to function as intended. In this view, educational institutions must prioritise human-in-the-loop designs and establish clear fallback mechanism to ensure that all AI tools undergo rigorous testing before deployment in real-world educational environments.

4.13. Deepfakes and misinformation

Another serious concern identified in this research relates to the growing threat of deepfakes and misinformation vastly facilitated by the increasingly powerful generative AI tools. The work of Karan and Angadi (2023) places emphasis on how the same technologies that enable personalised learning content and virtual teaching assistants can also be weaponised to create false or misleading information, potentially disrupting the integrity of academic environments. Deepfake technologies can be used to fabricate audio or video content that mimics the speech and likeness of public figures, instructors, or even students. In educational contexts, this could result in reputational damage, harassment, or the dissemination of falsified academic materials. Furthermore, generative AI models trained

on unverified data sources may inadvertently produce plausible-sounding but factually incorrect outputs, which students might accept as legitimate if not adequately trained in media literacy and source verification. The risk is compounded in digital classrooms where content verification mechanisms are often weak, and students rely heavily on AI-powered tools for information synthesis. Scholars argue that exposure to misinformation, especially without adequate critical thinking training, can undermine academic rigor and promote the spread of false narratives within scholarly communities (Karan and Angadi, 2023).

To combat these risks, institutions must incorporate AI literacy and media verification skills into their curricula, while regulators must adopt policies centred on the ethical use of generative AI tools that prohibit explicitly the manipulation of academic or personal content through deceptive AI-generated media, in order to promote transparency, fact-checking, and accountability which are essential to preserving trust in digital education environments.

4.14. Environmental impact

This research acknowledges the often-overlooked yet increasingly significant environmental impact of adopting generative AI technologies in higher education. Even though these systems offer considerable pedagogical advantages, they also require massive computational power, which translates into a substantial carbon footprint. In their study, Francis et al. (2024) argue that the training and operation of large language models (LLMs) includes those used in educational platforms and they all rely on energy-intensive data centres mainly powered by non-renewable energy sources, thereby raising concerns about the sustainability of widespread AI integration in academia. This is mostly caused by their backend operations which involve continuous server activity, complex inferencing, and frequent updates, despite their operations may appear “invisible” from a student or educator’s perspective. In fact, every interaction with generative AI-tools, from generating a lesson summary, to reviewing a student essay, or synthesising lecture notes, requires data processing on a scale far greater than conventional educational digital technologies. In consequence, the cumulative environmental cost of AI integration may undermine broader institutional efforts toward sustainable development goals (SDGs), notably SDG 13 on climate action.

Moreover, the allure of convenience and automation in education, as suggested by Gammoh (2025) and Karan and Angadi (2023), may further accelerate dependency on these instruments and inadvertently increase digital consumption patterns. If unchecked, this cycle poses ethical dilemmas about whether technological enhancement should be prioritised over environmental stewardship in academic decision-making. To mitigate this risk, Francis et al. (2024) recommend a dual-pronged approach, starting with encouraging the use of green AI practices, including energy-efficient models and carbon-offsetting protocols, and continuing with fostering awareness among academic stakeholders about the ecological consequences of AI use. Thus, universities must include environmental considerations in their digital strategies and promote transparency around the carbon costs of edtech tools through engaging in cross-sector collaborations that develop sustainable AI infrastructures.

5. Conclusions

This research paper carried out an investigation through a systematic literature review with the purpose of critically examining the perceived and observed risks associated with the integration of generative AI tools in higher education, with a particular emphasis on university-level teaching and learning environments. As previously outlined in the introduction section, the primary objective was to identify, synthesise, and evaluate a wide range of academic concerns, from ethical dilemmas and digital inequalities to psychological and pedagogical challenges, all emerging from recent literature on the topic.

Taking into account that this paper provides not only a taxonomy of risks related to AI integration into higher education landscapes, but also connects them with broader institutional and pedagogical implications and offer an integrative lens to understand AI's role in shaping the future of academia, this article contributes to the existing body of knowledge by providing one of the most up-to-date, detailed, and structured syntheses of AI-related educational risks to date. The analysis of fourteen core risk categories initially derived from the reviewed literature has been expanded and systematised into a comprehensive table now covering 23 distinct risk domains (Table 1). These domains range from academic integrity breaches and bias in AI-generated content, to lesser discussed yet equally critical concerns such as functional reliability, environmental impact, deepfakes, and the potential erosion of teacher authority. This synthesis reveals that the use of generative AI in higher education is not just a technological shift, but a complex cultural and institutional transformation that demands careful, context-sensitive governance and proactive mitigation strategies. Notably, this paper places emphasis on how the rapid adoption of AI tools has introduced tensions between pedagogical innovations and traditional educational values like critical thinking, autonomy, and equality.

Table 1. *Risks and challenges of generative AI use in higher education*

Theme	Main findings	Source
1. Academic integrity	Risk of plagiarism and diminished student originality due to AI-generated work	Francis et al. (2024); Gammoh (2025)
2. Assessment validity	Difficulty in verifying student-authored work and challenges for formative and summative evaluation	Karan and Angadi (2023); Gammoh (2025)
3. Skills erosion	Erosion of critical thinking, writing, and research skills; students may depend excessively on AI	Demir and Demir (2024); Francis et al. (2024)
4. Bias and inaccuracy	Generative AI reproduces societal, cultural, and data-driven biases; it may also provide incorrect or misleading outputs	George and Wooden, (2023); Karan and Angadi (2023); Gallent-Torres et al., (2024); Francis et al. (2024); Abulibdeh et al., (2025); Doğan et al., (2025); Mahmud et al., (2025)
5. Ethical concerns	Unclear authorship, opacity of algorithms, and lack of transparency in AI tools	Gallant-Torres et al., 2024; Lünich et al. (2024); Samman, 2024; Gammoh (2025); Sposato, (2025); Symeou et al., (2025)
6. Data privacy	Potential exploitation of student data; insufficient regulation of third-party platforms	Karan and Angadi (2023); Demir and Demir (2024);
7. Teacher preparedness	Inadequate training and institutional guidance; lack of pedagogical frameworks for AI integration	Karan and Angadi (2023); ; Gammoh (2025)
8. Pedagogical misalignment	AI-generated content may misalign with learning objectives; oversimplifies complex topics	Demir and Demir (2024); Francis et al. (2024)
9. Increased workload	Faculty staff face new demands in AI surveillance, assignment redesign, and policy updates	Gammoh (2025)

Theme	Main findings	Source
10. Digital divide	Students and institutions vary in access to reliable AI tools, amplifying educational inequality	Demir and Demir (2024); Francis et al. (2024)
11. Autonomy and control	Educators may feel disempowered; growing reliance on automated grading and feedback systems	Karan and Angadi (2023); Lünich et al. (2024)
12. Functional risks	Issues include AI hallucinations, outdated outputs, and lack of context-awareness	Karan and Angadi (2023)
13. Deepfakes and misinformation	AI-generated deepfakes and misinformative content threaten academic trust and authenticity	Karan and Angadi (2023)
14. Environmental impact	High energy use of large language models raises sustainability concerns	Francis et al. (2024)
15. Algorithmic opacity	Lack of explainability in AI decisions makes it difficult to audit errors or biases	Francis et al. (2024); Lünich et al. (2024)
16. Erosion of trust in education	Overuse of AI may lead students and faculty to question the authenticity of academic work	Karan and Angadi (2023); Francis et al. (2024)
17. Lack of institutional policies	Many institutions are still developing clear guidelines on AI use, leading to confusion	Demir and Demir (2024); Gammoh (2025)
18. Overdependence on automation	Automation of grading, feedback, and even content creation risks deskilling educators and oversimplifying instruction	Karan and Angadi (2023); Lünich et al. (2024)
19. Overstandardisation of learning	Reliance on generative AI can push education toward overly standardised, generic content, suppressing diversity in thinking and localised/ contextual knowledge	Karan and Angadi (2023); Demir and Demir (2024)
20. Reduced student motivation and engagement	Easy access to AI-generated answers may reduce the intrinsic motivation to learn, leading to passive learning habits and reduced classroom participation	Francis et al. (2024); Gammoh (2025)
21. Misuse for harassment or bullying	Generative AI can be misused by students to create harmful, offensive, or targeted deepfake content, especially in anonymous settings	Karan and Angadi (2023)
22. Curriculum obsolescence	Rapid AI development risks rendering current curricula outdated, requiring continual redesign that institutions may be unprepared to handle	Demir and Demir (2024); Gammoh (2025)
23. Teacher authority undermined	Students may challenge educators using AI-generated content as counter-arguments or "expert" information, potentially undermining the educators' authority and role.	Lünich et al. (2024); Gammoh (2025)

Source: Author's own contribution.

To sum up, despite the undeniable potential of generative AI-tools to enhance academic productivity and personalise learning experiences, it also presents multidimensional and underestimated risks, which must be mitigated through comprehensive institutional frameworks, adequate digital training, and continuous ethical oversight. Otherwise, these tools could inadvertently deepen existing inequalities, diminish student engagement, and strain faculty capacities. In this light, universities must move beyond reactive policies and invest in anticipatory strategies that account for both technological and social consequences.

Nonetheless, the scope of this study is limited by its dependence on a selected set of academic sources published between 2017 and 2025, predominantly in Western and Middle Eastern contexts. Future research should focus on comparative cross-country studies, longitudinal data collection on AI use in classrooms, and the co-creation of ethical guidelines with students and educators alike. In particular, more attention should be paid

to the intersection of AI use with gender, accessibility, and socio-economic backgrounds, because only through such multidimensional approaches can we ensure that AI becomes an inclusive, sustainable, and pedagogically aligned in higher education settings.

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Determining the differences in the absorption of EU funds between two European economies, Romania and Bulgaria

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Abstract. *The aim of this paper is to identify whether there are major differences in the absorption rate of funds between Romania and Bulgaria, and what factors determine these disparities. The analysis of the absorption rate is essential, as it assesses the capacity of a state or region to efficiently use the available financial resources, especially within the framework of the Cohesion Policy, which is considered the most important investment policy of the Union. In this case, ANOVA and a fixed-effects panel model were used for the period 2007–2020. Thus, covering the Multiannual Financial Frameworks 2007–2013 and 2014–2020, the results showed that, even though the absorption rates of the two countries are similar and show continuous progress, they remain below the European Union average. The research also makes a significant contribution to empirical studies on the factors influencing absorption capacity in these two economies.*

Keywords: European funds, absorption capacity, cohesion policy, ANOVA, panel data analysis.

JEL Classification: O52; C23; F36.

1. Introduction

Cohesion policy aims to establish the necessary conditions for the development of all European regions, with particular emphasis on those whose GDP per capita is below the European Union (EU) average. It provides resources (funds) to support development-related objectives and to address various issues that hinder the progress of these regions, such as unemployment, lack of infrastructure, and others.

Therefore, the absorption of funds is an essential factor in the European integration process, especially for the new member states of the Union, which expect to receive a considerable amount of funding from the EU budget and become net beneficiaries of accession.

Although the available funds represent a great opportunity for member states, this does not necessarily mean that they will be able to use them to their full capacity, as their impact depends on the ability to effectively “absorb” them (Kersan-Škabić and Tijanić, 2017).

Consequently, increased absorption capacity is widely seen as a key condition for enhancing the contribution of EU funds to economic and social cohesion. Taking into account that EU funding under cohesion policies plays a central role as the main investment instrument (particularly in Central and Eastern European Member States) this may explain the recent interest in understanding and analysing absorption capacity and the factors that influence it, in order to identify measures to increase it. (Marinaş & Prioteasa, 2016)

This paper aims to provide a comparison of the absorption rates of the Cohesion Fund (CF), European Social Fund (ESF), and European Regional Development Fund (ERDF), the main instruments of cohesion policy, for the period 2007–2020, covering the multiannual financial frameworks 2007–2013 and 2014–2020, in Romania and Bulgaria.

The goal of this comparison is that, if differences in fund absorption are identified, they may help reveal the factors driving these disparities. Moreover, both Romania and Bulgaria joined the EU in 2007, benefiting largely from the same financial instruments.

To perform this comparison, two widely used statistical methods were applied (ANOVA and panel data analysis) which, although different in purpose and applicability, are both frequently employed in research.

The paper is organized as follows: the next section provides a review of the literature; the third section details the data and methodology of the statistical analysis; the fourth section presents the results. Finally, the conclusions section summarizes the main findings in line with the article's objective.

2. Literature review

2.1. Theoretical framework regarding the absorption of European funds

The concept of absorption of funds has traditionally been defined as the capacity of a structure to spend the allocated funds. Also, the capacity to attract union funds is usually assessed by the “absorption rate,” this being an indicator calculated as a percentage of payments made from the allocated amounts (available funding) for a specific program, region, or country.

These definitions highlight the strong connection between absorption capacity and the process of allocating funds and implementing projects within individual operational programs (OPs). (Crescenzi, 2017)

On the other hand, Tosun (2014) emphasizes that absorption can be seen as a necessary condition for the effectiveness of funds, the absorption rate being assessed as an indicator of the performance of programs and constantly applied for cohesion policy analysis.

At the beginning of 2007, there was much discussion about how a company's budget should be structured, as European funds were a significant source of investment financing, especially in the new member states. A significant part of the budget is dedicated to cohesion policy for employment and economic growth. Considering cohesion finance as an investment instrument to stimulate development and competitiveness in many EU Member States, achieving a high absorption rate becomes an important issue for regional and national governments (Horvat & Maier, 2004).

Thus, authorities have taken steps to avoid and manage absorption capacity deficits and absorption obstacles (Kalman, 2002)

In the literature on the impact of EU funding, the so-called “absorption difficulties” that Member States need to take into account have been identified. Among the most important, according to Dragan (2008), are:

- administrative absorption problems leading to a discrepancy between funding from the EU budget and the development of productive capital in the beneficiary state/region; individuals who get involved in the management of EU funds to obtain personal benefits, manifesting themselves through external forms of corruption at various levels (e.g., between national governments, between authorities and various organisations wishing to access EU funds, etc.);
- EU investments in infrastructure projects are long-term public investments and can lead to significant short-term opportunity costs, such as delaying decisions on private investments or even crowding out private investments;
- if regional and central governments cannot establish a strict set of investment priorities, EU funding can be used inefficiently. The principle of additionality dictates how EU funds are used. This means that EU funds allocated to Member States are not a substitute for Member States' investment efforts but are additional to available national funding.

These obstacles need to be taken into account because they affect a country's ability to implement EU-funded initiatives and achieve the European strategic objectives for convergence. Therefore, absorption capacity is an important issue in cohesion policy. Percoco (2017) states that cohesion policy (CP) is the main way in which EU projects are financed. This is done by EU Member States and local authorities in collaboration, based on complex multi-level governance, to reduce disparities between regions in Europe.

The European Structural Funds (ESF) are the objective of the CP to promote the sustainable development of regions in terms of economic prosperity and quality of life. In line with this policy, the European Structural and Investment Funds (ESI) accounted for around a third of the total budget of the European Union between 2014 and 2020. These

funds included the Cohesion Fund (CF), the European Regional Development Fund (ERDF), the European Social Fund (ESF), and, for the time being, the Youth Employment Initiative (YEI) (Caldas et al., 2018).

2.2. The general challenges of Romania and Bulgaria in absorbing funds

In his work, Lucian (2021) states that Romania faced problems related to the absorption rate during both the 2007–2013 and 2014–2020 periods. The global financial crisis of 2008 affected several EU member states, including Romania, and between 2014 and 2020, two important events, Brexit and the pandemic, affected the common budget and overall progress.

A large number of actors and management authorities involved in the process and a lack of efficiency and coordination between ministries, civil society, the business environment and research and development institutes are among the factors that contributed to the low absorption rate in Romania.

The increase in corruption practices and the lack of trust of the private sector in the use of structural funds are other reasons for the low level of absorption of European funds. (Zaman & Cristea, 2011)

In the case of Bulgaria, the situation was similar: at the time of EU accession on 1 January 2007, the country's government lacked the administrative capacity to rapidly use structural aid funds. Bulgaria's low initial absorption rate is an example of several shortcomings.

First, due to differences in the information management system, compliance reporting and control systems at the central government level did not comply with EC requirements. Project implementation was hampered by complicated application procedures, administrative burdens, and complex guidance processes. (Paliova & Lybek, 2014) Since the start of the 2014–2020 programme, absorption has increased. This demonstrates that the government placed great emphasis on increasing absorption, even appointing a special minister for EU funds.

According to the European Parliament report (2024), several solutions have been adopted in Bulgaria to address the implementation obstacles. These include investing in training; promoting digitalisation at different phases of the project cycle, including reporting; improving the selection of operations through a sound intervention logic and an adequate needs analysis; introducing specific rules aimed at motivating the structures managing EU funds to apply a more efficient and effective approach to work (e.g., deadlines for the execution of tasks in the context of project cycle management duration of the evaluation, period for carrying out checks, etc.); and "staggering" investments to streamline implementation.

3. Methodology and Data

The aim of this paper is to identify whether there are major differences in the absorption rate of EU funds between Romania and Bulgaria, and what factors determine these disparities.

In this case, we used ANOVA; this model was chosen due to its ability to perform multiple simultaneous comparisons between countries, allowing us to distinguish the differences. ANOVA has also been used by other authors, such as Šostar et al. (2023), who had as their research subject the absorption of EU funds and their impact on the regional development of Croatia, Slovenia, Hungary, and Poland.

We opted for the countries of Romania and Bulgaria because both joined the EU in 2007, benefiting largely from the same financial instruments, and a comparison between the two, in case differences in fund absorption are highlighted, can lead to the identification of the factors that influence these differences.

In addition, we wanted to analyze the effect of the years, so we continued the research with a fixed-effects panel model for a more detailed analysis. In many cases, the fixed-effects methodology is used for panel analysis with few explanatory variables. Thus, the problem of omitted variables is avoided. (Albulescu & Goyeau, 2013)

Also, as stated by Baldwin and Taglioni (2006), in the case of temporary fixed effects, all unobserved characteristics that fluctuate over time but are common to all countries are taken into account.

Regarding the data on the absorption of funds for Romania and Bulgaria, these were calculated based on European Commission data as a ratio between payments made and the total allocation of CF, ESF and ERDF funds for the period 2007–2020. Thus, covering the multiannual financial frameworks 2007–2013 and 2014–2020, respectively.

The research stops at closed budgetary periods because the absorption rate is concrete or almost completed, providing a complete evaluation framework.

Therefore, the model equation was in the form:

$$\text{Rata_abs} = \beta_0 + \beta_1 \times \text{DUM_RO} + \beta_2 \times \text{YEAR} + \varepsilon \quad (1)$$

Where: *rata_abs* represents the absorption rate, *dum_ro* is the dummy variable for Romania, *year* the calendar year, and β_0 the intercept; β_1 , β_2 the regression coefficients.

The data was processed using statistical data analysis software EViews 12.

4. Results and Discussion

Table 1. ANOVA and T-tests for comparing the means of absorption rates

Method	df	Value	Probability
t-test	26	0.420805	0.6774
Satterthwaite-Welch t-test*	25.94474	0.420805	0.6774
ANOVA F-test	(1,26)	0.177077	0.6774
Welch F-test*	(1,25.9447)	0.177077	0.6774
<i>Analysis of Variance</i>			
Source of Variation	df	Sum of Sq.	Mean Sq.
Between	1	0.025483	0.025483
Within	26	3.741606	0.143908
Total	27	3.767089	0.139522

*Test allows for unequal cell variances

Source: Authors' own data processing in Eviews 12

Table 1 presents the results of the ANOVA test and the T-test in order to compare the absorption rates of funds between Romania and Bulgaria. They show that there are no statistically significant differences between the two countries ($p = 0.6774$ in all applied tests). The high values of the p-test indicate that the variation observed between the two groups is insignificant and can be attributed to random fluctuations. Thus, we can say that during the analyzed period, Romania and Bulgaria recorded similar absorption rates of European funds.

Table 2. *Fixed effect panel data model results*

Regression statistics: R2= 0.9718; Adjusted R2= 0.9683; F-statistic= 276.2570; Prob (F-statistic)= 0.000000				
Variables	Coefficient	Std. Error	T-Statistic	Prob.
C	-113.5937	12.6453	-8.9830	0.000
Dum_Ro	0.0603	0.0251	2.4017	0.024
Year	0.0566	0.0062	9.0220	0.000

Source: Authors' own data processing in *Eviews 12*

The results obtained in Table 2 indicate that Romania has an average absorption rate approximately 6 percentage points higher than Bulgaria during the analyzed period. This result is statistically significant, being below the 0.05 threshold. Regarding the evolution over time, the coefficient associated with the variable year has a value of 0.0566, which signals an average annual increase of 5.67 percentage points in the absorption rate, a trend that is also statistically significant. This result suggests that both countries have registered constant progress in the absorption of EU funds over the period.

The model has a high explanatory power, with an R-squared of 0.9718, which indicates that over 97% of the variation in the absorption rate is explained by the variables included in the model. In addition, the F-statistic value, together with a p-value close to zero, shows that the model is significant.

The results obtained are also supported by the European Parliament report (2024) entitled Absorption rates of Cohesion Policy funds, which highlights the idea that the absorption rate in 2014–2020 was consistently lower than in 2007–2013.

For example, at the end of 2020, the absorption rate was ten percentage points lower than the absorption rate in the previous programming period, at the end of 2013. This happens in most countries, with the exception of Romania, the Czech Republic, and Hungary.

Also, in the period 2007–2013, Romania had a lower absorption rate (the lowest at EU level) than Bulgaria, but both were below the EU average and the countries in the region. In the following period, Romania made significant progress. Even though the absorption rate of the two countries is similar and in continuous progress, they are still below the EU average.

At European level, certain barriers have been identified that hinder the absorption of funds, including: low levels of infrastructure and innovation development, low investment, vulnerability to external crises, low exposure or capacity to benefit from knowledge spillovers, limited workforce capacity; as well as inefficient institutional structures, training gaps, and insufficient digitalization.

In Romania and Bulgaria, obstacles are encountered in large infrastructure projects, which require a longer time for technical preparation, documentation, procurement, execution, and final approval. Frequent changes in national regulations are also considered a cause of delay and uncertainty. Other obstacles have an external origin, such as the pandemic and the war in Ukraine.

Internal solutions aimed at overcoming absorption obstacles, recommended by the EU, include reducing co-financing rates, reprogramming, phasing of projects, more intensive use of digitalization, improving operations selection processes and practices, strengthening human resources, reorganizing the governance of cohesion policy, etc. (European Parliament, 2024)

5. Conclusions

The absorption of funds is an essential factor in the European integration process, especially for the new member states of the Union, which expect to receive a considerable amount of funding from the EU budget and become net beneficiaries following accession. Romania and Bulgaria joined the EU in the same year, facing similar problems regarding the absorption of funds.

Firstly, due to differences in the information management systems, the compliance reporting and control mechanisms at the central government level did not meet EU requirements. Project implementation was hindered by complicated application procedures, administrative burdens, and complex guidance processes.

In this article, we carried out a comparative analysis between Romania and Bulgaria for the period 2007–2020, covering the multiannual financial frameworks 2007–2013 and 2014–2020. The absorption rate was calculated for the CF, ESF, and ERDF, which are the main funds of cohesion policy and the primary means of financing EU projects.

The results of the two econometric models highlighted that, for the analyzed period, there are no significant differences between the two countries. Nevertheless, Romania recorded an average absorption rate approximately 6 percentage points higher than Bulgaria.

Although the absorption rate of the two countries is similar and shows continuous progress, it remains below the EU average. Both countries have taken effective measures to improve the absorption of EU funds, but additional efforts could contribute to ensuring a more effective, efficient, and timely absorption in the next programming period.

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The interplay between fiscal policy and public debt using a Structural Vector Autoregression Model: a comparative study of Romania and the Czech Republic

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Abstract. *This Structural Vector Autoregression (SVAR) study investigates fiscal-monetary interactions in Romania and the Czech Republic over the period 1995–2023 focusing on GDP growth, government debt, spending, interest rates, and tax revenue. In Romania, GDP growth significantly reduces debt, while spending raises interest rates, suggesting crowding-out. In the Czech Republic, growth mildly reduces debt, and spending lowers interest rates, indicating monetary accommodation. Tax revenue shocks notably stimulate Czech GDP. These findings highlight divergent fiscal dynamics in CEE, informing debt sustainability strategies. Results align with fiscal adjustment theories, offering policy insights for EU economies balancing growth and stability.*

Keywords: fiscal policy, public debt, SVAR model, debt sustainability, comparative analysis.

JEL Classification: C32, E62, E52, H63.

1. Introduction

Fiscal policy plays a pivotal role in shaping economic outcomes, particularly in Central and Eastern European (CEE) countries that have undergone significant structural transformations since the 1990s. Romania and the Czech Republic, both EU members, offer a compelling contrast: Romania has pursued expansionary fiscal policies to boost growth, often at the cost of rising public debt, while the Czech Republic has maintained a more conservative stance, prioritizing debt sustainability. Understanding how fiscal shocks—such as changes in government spending, tax revenue, and interest rates—affect public debt and GDP growth is crucial for policymakers navigating post-transition challenges and external shocks, including the 2008 financial crisis and the COVID-19 pandemic.

This study employs a Structural Vector Autoregression (SVAR) model to examine the contemporaneous and dynamic effects of fiscal policy shocks on key macroeconomic variables in Romania and the Czech Republic (1995–2023). By comparing these two economies, we address a gap in the literature: while individual country studies exist, comparative analyses using SVAR to explore fiscal-debt dynamics in CEE remain scarce.

Our research question is: *How does fiscal policy shock influence public debt sustainability and economic growth in Romania and the Czech Republic, and what explains their divergent outcomes?*

This question comes from current need of comparative analysis between different CEE countries taking in consideration their specific fiscal and monetary strategies.

The article contributes to the scientific community by offering a methodologically rigorous, data-driven comparison, appealing to economists interested in fiscal policy, time-series econometrics, and CEE economic development.

2. Literature review

The interplay between fiscal policy and public debt has been a focal point in economic research. Bohn (1998) introduced fiscal reaction functions, arguing that sustainable debt requires governments to adjust primary balances as debt rises. Afonso and Jalles (2013) applied this framework to panel data, finding that fiscal sustainability depends on economic and institutional factors. Also, Afonso and Leal, (2019) showed how different fiscal values can vary according to the public debt level, the pace of economic growth, and the output gap, however the study was focused on Eurozone countries until 2016. In Central and Eastern Europe (CEE), Mackiewicz-Łyziak (2015) noted challenges of fiscal dominance, where debt pressures limit policy flexibility.

For Romania and the Czech Republic, recent studies by the International Monetary Fund (IMF, 2023, 2024) and the European Commission (2024) document show divergent fiscal paths. Romania's expansionary policies have spurred growth but increased debt, while the Czech Republic's conservative measures have kept debt stable. Structural Vector Autoregression models have been widely used to study fiscal dynamics (e.g., Blanchard & Perotti, 2002), offering a robust method to capture dynamic relationships.

There are several studies which examine the impact of fiscal rules on fiscal policy in Romania, noting an increase in public debt that threatens fiscal sustainability (Daniela Vodă et al., 2020). Another study uses the Synthetic Control Method to estimate the effect of expansionary fiscal measures on GDP growth in Romania (Boiciuc & Orțan, 2020). Additionally, some research focuses on fiscal policy sustainability in Romania during financial crises (Dornean & Oanea, 2015). Another paper studies the effects of fiscal policy shocks on the business environment in several Central and Eastern European countries, including the Czech Republic and Romania, (Dobrotă et al., 2021), however none is using our research variables together with SVAR method, as a comparison between two countries which start from similar values of variables and due to different approaches during the post-2008 crisis and COVID-19 timeframe, they get different results. We focus on these results into our research to create a possible framework for future studies and monetary and fiscal strategies, according to the countries specific background.

Despite this body of work, gaps remain in comparative analyses of CEE countries using SVAR models. This study fills this gap by focusing on Romania and the Czech Republic, contributing a nuanced understanding of how fiscal policy shapes debt in transitioning economies. Its novelty lies in its application of SVAR to these specific cases, providing empirical evidence for policy debates.

3. Methodology

This research employs a Structural Vector Autoregression (SVAR) model to analyse the effects of fiscal policy on public debt dynamics. The objectives are twofold: (1) to quantify the impact of fiscal shocks on debt levels in Romania and the Czech Republic, and (2) to assess the implications for debt sustainability.

The SVAR model uses yearly data from 1995 to 2023, sourced from national statistical offices, the European Commission's AMECO database, World Bank, OECD, Our Data in World and the IMF World Economic. Variables include:

- *Government Spending*: Total expenditure as a percentage of GDP.
- *Tax Revenue*: Total tax revenue as a percentage of GDP.
- *Public Debt*: Gross debt as a percentage of GDP.
- *GDP growth*: Annual real growth of GDP.
- *Interest Rates*: Average government bond yield.

The SVAR model is specified as:

$$A_0 y_t = A_1 y_{t-1} + \dots + A_k y_{t-k} + \varepsilon_t \quad (1)$$

Where y_t is a vector of the five variables, A_0 captures contemporaneous relationships, A_1 to A_k are lag coefficients and ε_t is a vector of structural shocks. The model is identified using short-run restrictions via Cholesky decomposition, with the variable ordering: GDP growth $\rightarrow$ government spending $\rightarrow$ tax revenue $\rightarrow$ public debt $\rightarrow$ interest rates. This reflects the assumption that GDP affects fiscal variables contemporaneously, while debt and interest rates respond with a lag.

The model is estimated in EViews version 12, following these steps:

- Import data and test for stationarity, applying transformations if needed.
- Estimate a VAR model and select the optimal lag length using AIC or BIC.
- Impose SVAR restrictions and generate impulse response functions (IRFs) to assess the dynamic effects of fiscal shocks over a 5-years horizon.
- Conduct variance decomposition to evaluate shock contributions to debt variability.

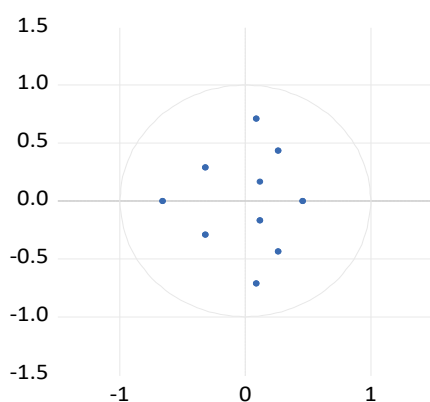
4. Results and discussions

We start with checking the stationarity of our variables. VAR models assume that all variables are stationary (i.e., their statistical properties don't change over time). Non-stationary data can lead to misleading results. Thus we check and get that our RO_GDP_growth, RO_interest_rate, RO_tax_revenue and RO_GOV_spend are I(1) variables and RO_GOV_debt is I(2) variable. For Czech Republic we have I(0) variable for CZ_GDP_growth and I(1) variables for CZ_GOV_debt, CZ_GOV_spend, CZ_interest_rates and CZ_tax_revenue.

We transform all corresponding variables to I(0) and proceed with VAR estimation.

Figure 1. Czech inverse roots of AR Characteristic Polynomial

Inverse Roots of AR Characteristic Polynomial



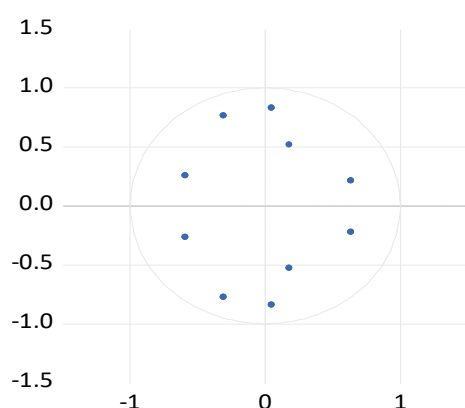
Source: Data from Eviews 12 (own contribution).

The lag structure we set at 2 and the Figure 1 and 2 show the AR roots are within the circle, thus we have a stable model for each of our considered countries. We have chosen these 2 countries because if we analyse the statistical time series, we see that initially we had similar GDP growth and similar interest rates, however some policies were different and now we have different outcomes in terms of our researched variables. We consider these countries to be a starting point for other countries within EU space and to be a learning point for the local policy makers regarding the fiscal and monetary policies. Each of these countries was managed differently and thus got a different outcome. By using SVAR we want to show how different shocks or impulses can influence our variables and how the policies can be modified based on these inputs.

Utilizing annual data from 1998 to 2022, the model is estimated via maximum likelihood with Cholesky decomposition for identification, imposing a recursive structure that allows for contemporaneous influences among the variables. The analysis further employs accumulated impulse response functions (IRFs) over five periods to assess the cumulative effects of structural shocks, with standard errors derived from 10,000 Monte Carlo replications.

Figure 2. Romanian inverse roots of AR Characteristic Polynomial

Inverse Roots of AR Characteristic Polynomial



Source: Data from Eviews 12 (own contribution).

For Czech Republic (Table 1) the estimated contemporaneous relationships, encapsulated in the F matrix, reveal significant interactions among the macroeconomic variables.

A positive shock to GDP growth results in a significant reduction in government debt ($C(2) = -1.120984$, $p < 0.001$), indicating that economic expansion alleviates fiscal pressures through mechanisms such as increased GDP or enhanced debt repayment capabilities. Furthermore, GDP growth appears to exert a marginally positive effect on interest rates ($C(4) = 0.389241$, $p = 0.0629$), potentially attributed to increased credit demand or heightened inflation expectations.

Conversely, an escalation in government debt leads to an immediate contraction in government spending ($C(7) = -0.670483$, $p = 0.0506$), suggesting a policy response aimed at ensuring fiscal sustainability. Notably, a government spending shock induces a reduction in both interest rates ($C(11) = -0.716202$, $p < 0.001$) and tax revenue ($C(12) = -2.707441$, $p < 0.001$). The decline in interest rates contradicts conventional expectations, as fiscal expansion typically raises rates through crowding-out effects; this may indicate an accommodating monetary policy environment. The reduction in tax revenue suggests reliance on deficit financing rather than immediate tax adjustments.

We further analyse the Dynamic Effects via Accumulated Impulse Response Functions (IRFs) for Czech Republic (Table 2) and Romania (Table 4).

The IRFs provide insights into medium-term responses to structural shocks, with standard errors indicated in parentheses.

Shock to GDP Growth (Shock1): A positive GDP growth shock continuously reduces government debt (-1.089409 by period 5, SE = 3.65644) and interest rates (-1.155619, SE = 1.43260), although the standard errors suggest statistical insignificance by period 5. Initially, tax revenue experiences an uptick (0.548499, SE = 0.08116) but stabilizes at a higher level (0.722298, SE = 0.65353), reinforcing the notion of growth's stabilizing fiscal role.

Table 1. SVAR Czech estimates

Structural VAR Estimates

Date: 04/11/25 Time: 21:06

Sample (adjusted): 1998 2022

Included observations: 25 after adjustments

Estimation method: Maximum likelihood via Newton-Raphson (analytic derivatives)

Convergence achieved after 21 iterations

Structural VAR is just-identified

Model: $e = \Phi u$ where $E[uu'] = I$

F =

C(1)	0	0	0	0
C(2)	C(6)	0	0	0
C(3)	C(7)	C(10)	0	0
C(4)	C(8)	C(11)	C(13)	0
C(5)	C(9)	C(12)	C(14)	C(15)

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.719041	0.101688	7.071067	0.0000
C(2)	-1.120984	0.241363	-4.644400	0.0000
C(3)	0.277198	0.357969	0.774362	0.4387
C(4)	0.389241	0.209321	1.859546	0.0629
C(5)	-1.118268	0.822213	-1.360070	0.1738
C(6)	0.909997	0.128693	7.071067	0.0000
C(7)	-0.670483	0.342949	-1.955050	0.0506
C(8)	0.074695	0.201676	0.370371	0.7111
C(9)	0.578615	0.802701	0.720835	0.4710
C(10)	1.647902	0.233049	7.071067	0.0000
C(11)	-0.716202	0.174077	-4.114280	0.0000
C(12)	-2.707441	0.700734	-3.863723	0.0001
C(13)	0.707883	0.100110	7.071067	0.0000
C(14)	0.160276	0.586438	0.273305	0.7846
C(15)	2.929998	0.414364	7.071067	0.0000

Log likelihood -204.4675

Estimated S matrix:

0.548499	0.083568	-0.068564	-0.035615	0.031515
-0.687385	1.148121	0.673759	-0.413717	-0.608446
0.838278	-0.865223	1.438076	0.782138	-0.444511
0.476876	0.453257	-0.477276	0.586197	-0.280032
-1.062897	1.567296	-1.450081	-0.576605	2.411546

Estimated F matrix:

0.719041	0.000000	0.000000	0.000000	0.000000
-1.120984	0.909997	0.000000	0.000000	0.000000
0.277198	-0.670483	1.647902	0.000000	0.000000
0.389241	0.074695	-0.716202	0.707883	0.000000
-1.118268	0.578615	-2.707441	0.160276	2.929998

Source: Data from Eviews 12. (own contribution).

Table 2. Impulse analysis of Czech SVAR

Accumulated Response of CZ_GDP_GROWTH:					
Period	Shock1	Shock2	Shock3	Shock4	Shock5
1	-1.062897 (0.66461)	1.567296 (0.61166)	-1.450081 (0.53710)	-0.576605 (0.48795)	2.411546 (0.34211)
2	-1.187425 (1.34794)	1.033997 (1.24318)	-1.883688 (1.20757)	-0.543116 (1.06825)	3.035416 (0.96037)
3	-1.174531 (2.08739)	0.626163 (1.76866)	-2.792126 (1.78026)	0.210370 (1.51726)	3.176802 (1.43771)
4	-1.027099 (2.83600)	0.292779 (2.15225)	-2.824988 (2.40763)	0.322801 (1.93045)	2.852749 (2.08030)
5	-1.089409 (3.65644)	0.510340 (2.44061)	-2.758928 (3.06895)	0.178250 (2.26359)	2.942183 (2.56379)
Accumulated Response of D(CZ_GOV_DEBT):					
Period	Shock1	Shock2	Shock3	Shock4	Shock5
1	0.476876 (0.19638)	0.453257 (0.17461)	-0.477276 (0.14621)	0.586197 (0.10037)	-0.280032 (0.03973)
2	0.525798 (0.42028)	0.037328 (0.38033)	-0.697031 (0.36818)	0.934361 (0.30029)	-0.120641 (0.26245)
3	0.352757 (0.63426)	-0.039720 (0.52156)	-0.734107 (0.53857)	0.751084 (0.45251)	-0.022081 (0.42555)
4	0.349146 (0.83711)	0.082958 (0.61039)	-0.699917 (0.68070)	0.604108 (0.57325)	0.081446 (0.57498)
5	0.381665 (1.06002)	0.140600 (0.67201)	-0.670457 (0.85739)	0.638348 (0.67199)	0.023725 (0.67284)
Accumulated Response of D(CZ_GOV_SPEND):					
Period	Shock1	Shock2	Shock3	Shock4	Shock5
1	0.838278 (0.40092)	-0.865223 (0.35651)	1.438076 (0.27188)	0.782138 (0.14234)	-0.444511 (0.06306)
2	0.193989 (0.77855)	-0.649334 (0.70768)	1.660770 (0.66961)	0.354803 (0.54671)	-0.558969 (0.51970)
3	0.163695 (1.10074)	-0.701372 (0.90073)	1.609709 (0.91078)	-0.052799 (0.74028)	0.133601 (0.73211)
4	0.120288 (1.38648)	-0.542429 (1.04087)	1.765342 (1.16092)	-0.279113 (0.89497)	0.211941 (0.97509)
5	0.248661 (1.71829)	-0.584317 (1.15076)	1.623401 (1.44827)	-0.023917 (1.00710)	0.065520 (1.12764)
Accumulated Response of D(CZ_INTEREST_RATES):					
Period	Shock1	Shock2	Shock3	Shock4	Shock5
1	-0.687385 (0.32068)	1.148121 (0.25874)	0.673759 (0.17677)	-0.413717 (0.13412)	-0.608446 (0.08632)
2	-0.790718 (0.61990)	1.217095 (0.52636)	0.324822 (0.49891)	0.054306 (0.43988)	-0.483181 (0.41617)
3	-0.992459 (0.88205)	0.855600 (0.69211)	0.115552 (0.70834)	0.161606 (0.60096)	-0.222935 (0.60194)
4	-1.156157 (1.12128)	0.853722 (0.79664)	0.038079 (0.89014)	-0.040738 (0.72520)	0.012375 (0.79131)
5	-1.155619 (1.43260)	0.959006 (0.90342)	0.064215 (1.11179)	-0.133245 (0.84278)	0.068448 (0.90839)
Accumulated Response of D(CZ_TAX_REV):					
Period	Shock1	Shock2	Shock3	Shock4	Shock5
1	0.548499 (0.08116)	0.083568 (0.02021)	-0.068564 (0.01359)	-0.035615 (0.00808)	0.031515 (0.00447)
2	0.602834 (0.20528)	0.048687 (0.16785)	-0.053934 (0.16775)	-0.032100 (0.15144)	0.230536 (0.14241)
3	0.647746 (0.32965)	-0.005422 (0.24548)	-0.033580 (0.25974)	-0.025581 (0.22399)	0.048900 (0.21827)
4	0.719240 (0.47018)	-0.038660 (0.30923)	-0.091164 (0.35468)	0.059437 (0.29145)	0.050419 (0.30928)
5	0.722298 (0.65353)	-0.028692 (0.36000)	-0.004014 (0.47137)	0.004666 (0.35635)	-0.017221 (0.38271)

Structural VAR

Standard errors: Monte Carlo (10000 repetitions)

Source: Data from Eviews 12. (own contribution)

Shock to Government Debt (Shock2): An initial debt shock prompts an increase in government spending (-0.865223, SE = 0.35651, period 1), which subsequently reverses to a contraction by period 5 (-0.584317, SE = 1.15076), indicating a delayed fiscal adjustment. Interest rates consistently rise (0.959006, SE = 0.90342), aligning with the implications of higher borrowing costs.

Table 3. SVAR Romanian estimates

Structural VAR Estimates

Date: 04/11/25 Time: 18:02

Sample (adjusted): 2005 2022

Included observations: 18 after adjustments

Estimation method: Maximum likelihood via Newton-Raphson (analytic derivatives)

Convergence achieved after 23 iterations

Structural VAR is just-identified

Model: $e = \Phi \cdot F_u$ where $E[uu'] = I$

F =

C(1)	0	0	0	0
C(2)	C(6)	0	0	0
C(3)	C(7)	C(10)	0	0
C(4)	C(8)	C(11)	C(13)	0
C(5)	C(9)	C(12)	C(14)	C(15)

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	3.226860	0.537810	6.000000	0.0000
C(2)	-3.474253	0.674954	-5.147392	0.0000
C(3)	-1.625567	0.347668	-4.675625	0.0000
C(4)	-1.505678	1.294514	-1.163122	0.2448
C(5)	1.160042	0.385441	3.009645	0.0026
C(6)	1.471366	0.245228	5.999999	0.0000
C(7)	0.222308	0.214706	1.035405	0.3005
C(8)	-1.845595	1.232142	-1.497875	0.1342
C(9)	-0.259942	0.330617	-0.786234	0.4317
C(10)	0.897254	0.149542	5.999999	0.0000
C(11)	1.790367	1.155214	1.549814	0.1212
C(12)	-0.525563	0.315845	-1.663990	0.0961
C(13)	4.734831	0.789139	5.999999	0.0000
C(14)	-0.778217	0.274340	-2.836685	0.0046
C(15)	1.025629	0.170938	5.999999	0.0000

Log likelihood -191.5447

Estimated S matrix:

2.931065	1.104199	0.315223	3.851953	-1.732368
-4.175249	0.177272	0.794057	-1.585715	2.702098
-0.724072	-0.492067	0.889668	-0.747683	0.957264
-0.052839	-1.528623	0.382308	2.689016	0.266192
0.912506	-0.048626	-0.336840	-0.455840	0.521469

Estimated F matrix:

3.226860	0.000000	0.000000	0.000000	0.000000
-3.474253	1.471366	0.000000	0.000000	0.000000
-1.625567	0.222308	0.897254	0.000000	0.000000
-1.505678	-1.845595	1.790367	4.734831	0.000000
1.160042	-0.259942	-0.525563	-0.778217	1.025629

Source: Data from Eviews 12. (own contribution)

Shock to Government Spending (Shock3): This shock leads to an initial increase in GDP growth (-1.450081, SE = 0.53710) but presents a counterintuitive negative cumulative effect by period 5 (-2.758928, SE = 3.06895), suggesting potential mis-specification of the

model. Interest rates initially rise (0.673759, SE = 0.17677) but diminish thereafter (0.064215, SE = 1.11179), while tax revenue remains largely unresponsive (-0.004014, SE = 0.47137).

Shock to Interest Rates (Shock4): The effects observed here are weak, with a slight positive impact on government debt (0.638348, SE = 0.67199) by period 5, but most responses, including GDP growth (0.178250, SE = 2.26359), are statistically insignificant, indicating limited fiscal transmission.

Shock to Tax Revenue (Shock5): A tax revenue shock appears to stimulate GDP growth (2.942183, SE = 2.56379) by period 5, potentially reflecting the effects of stimulative tax cuts. However, its effects on other variables, such as debt (0.023725, SE = 0.67284), are negligible. Also, the Cholesky identification approach assumes unidirectional contemporaneous effects, potentially overlooking bidirectional dynamics, such as the influence of interest rates on GDP growth. The relatively small sample size (25 observations) coupled with significant standard errors in later IRF periods (e.g., GDP growth in response to Shock1: SE = 3.65644) limits the statistical power of the analysis. Furthermore, counterintuitive results, including negative GDP responses to spending shocks, suggest specification issues, which may arise from variable ordering or omitted variable biases.

For Romania (Table 3) the F matrix, a lower triangular matrix, captures these immediate effects, with diagonal elements (e.g., C(1), C(6), C(10), C(13), C(15)) representing the standard deviations of structural shocks, all highly significant ($p < 0.001$), indicating well-identified shocks. Off-diagonal elements reveal the contemporaneous impacts of these shocks, with significance levels ($p < 0.05$) denoting robust relationships and higher p-values indicating weaker or insignificant effects.

Regarding the key contemporaneous effect, we can econometrically interpret the following data for Romania.

Government Debt (C(2) = -3.474253, $p < 0.001$): A one-unit increase in GDP growth reduces government debt by 3.47 units, reflecting growth's ability to lower debt-to-GDP ratios through higher denominators or fiscal surpluses during booms.

Government Spending (C(3) = -1.625567, $p < 0.001$): Growth reduces spending by 1.63 units, possibly due to automatic stabilizers (e.g., reduced welfare payments) or countercyclical fiscal policies.

Interest Rates (C(4) = -1.505678, $p = 0.2448$): An insignificant negative effect suggests a potential monetary easing following growth, though evidence is weak.

Tax Revenue (C(5) = 1.160042, $p = 0.0026$): Growth boosts tax revenue by 1.16 units, consistent with increased economic activity enhancing collections.

Regarding the Government Debt Shock we can draw the following conclusions.

Table 4. *Impulse analysis of Romanian SVAR*

Accumulated Response of D(RO_GOV_DEBT,2):					
Period	Shock1	Shock2	Shock3	Shock4	Shock5
1	-4.175249 (1.02663)	0.177272 (0.76396)	0.794057 (0.75735)	-1.585715 (0.68430)	2.702098 (0.44608)
2	-1.551670 (2.55850)	0.381447 (2.19646)	-2.919393 (2.33158)	0.819049 (2.40410)	3.161486 (2.02666)
3	-2.607102 (3.89776)	1.712986 (3.12795)	-0.222708 (3.40866)	1.101098 (3.55661)	-0.077006 (3.25095)
4	-4.186753 (5.78208)	1.269417 (4.41957)	1.513413 (5.14509)	0.730358 (5.15876)	-0.363069 (4.63579)
5	-3.734113 (9.47949)	1.221016 (6.99667)	-0.212785 (7.63844)	-0.470395 (8.33277)	0.075934 (7.10592)

Accumulated Response of D(RO_GOV_SPEND):					
Period	Shock1	Shock2	Shock3	Shock4	Shock5
1	-0.724072 (0.39033)	-0.492067 (0.36352)	0.889668 (0.32595)	-0.747683 (0.25609)	0.957264 (0.15803)
2	-0.778199 (0.81862)	-0.378995 (0.70164)	0.444951 (0.76207)	-0.148048 (0.80329)	1.151166 (0.68057)
3	-1.488846 (1.33968)	0.086767 (1.08417)	0.628415 (1.14243)	0.147240 (1.20955)	0.725199 (1.10679)
4	-1.420920 (2.01738)	0.113913 (1.62867)	0.637156 (1.84238)	0.385104 (1.94883)	0.303013 (1.68713)
5	-1.582776 (3.24366)	0.188651 (2.62020)	1.036426 (2.73211)	0.182781 (3.17697)	-0.216547 (2.66110)

Accumulated Response of D(RO_INTEREST_RATES):					
Period	Shock1	Shock2	Shock3	Shock4	Shock5
1	-0.052839 (0.73941)	-1.528623 (0.69286)	0.382308 (0.64080)	2.689016 (0.45292)	0.266192 (0.04394)
2	0.425868 (1.57680)	-1.544438 (1.35576)	0.250117 (1.47836)	3.009292 (1.44720)	0.375326 (1.14249)
3	-0.383972 (2.81159)	-2.097775 (2.33215)	1.466915 (2.45092)	3.801722 (2.51865)	0.761926 (2.07693)
4	-0.361498 (4.44519)	-2.078394 (3.76545)	0.962806 (4.04319)	3.884128 (4.65971)	0.991122 (3.40226)
5	-0.954378 (7.84748)	-2.115685 (6.61179)	1.362553 (6.35848)	4.445089 (8.97303)	0.641390 (5.58327)

Accumulated Response of D(RO_TAX_REV):					
Period	Shock1	Shock2	Shock3	Shock4	Shock5
1	0.912506 (0.23542)	-0.048626 (0.18256)	-0.336840 (0.17331)	-0.455840 (0.14364)	0.521469 (0.08609)
2	1.013740 (0.61433)	-0.143716 (0.51189)	-0.160506 (0.56393)	-0.969400 (0.56372)	0.675655 (0.44983)
3	0.909783 (1.15020)	-0.256609 (0.90448)	-0.367020 (0.97782)	-0.988220 (1.02124)	0.936903 (0.89952)
4	1.122672 (1.86014)	-0.208232 (1.46925)	-0.736725 (1.60449)	-0.816723 (1.73519)	1.086657 (1.48194)
5	1.273858 (3.24117)	-0.181030 (2.51128)	-0.619811 (2.46387)	-0.713285 (3.03084)	0.997762 (2.47261)

Accumulated Response of D(RO_GDP_REAL):					
Period	Shock1	Shock2	Shock3	Shock4	Shock5
1	2.931065 (1.13229)	1.104199 (1.01510)	0.315223 (1.00427)	3.851953 (0.76012)	-1.732368 (0.28599)
2	1.772822 (2.41465)	1.528892 (2.04518)	1.921562 (2.23384)	-0.898263 (2.32145)	-1.822347 (1.97831)
3	2.587697 (3.60044)	-0.594005 (2.92388)	0.365940 (3.18526)	-1.209037 (3.39270)	-0.861503 (3.02894)
4	2.693008 (5.30240)	0.160354 (3.99066)	-0.179047 (4.60741)	0.088458 (5.28495)	-0.717729 (4.33436)
5	2.979868 (8.39910)	0.454152 (6.38527)	0.016748 (6.76052)	0.659285 (9.61283)	0.552961 (6.75939)

Structural VAR
Standard errors: Monte Carlo (10000 repetitions)

Source: Data from Eviews 12. (own contribution)

Interest Rates (C(8) = -1.845595, $p = 0.1342$): A marginally negative but insignificant effect hints that rising debt might lower interest rates, possibly due to monetary policy responses, though not strongly supported.

Tax Revenue (C(9) = -0.259942, $p = 0.4317$): An insignificant negative effect suggests no immediate fiscal adjustment via taxes following debt increases.

If we look at Government Spending Shock we can interpret the data as follows.

Interest Rates (C(11) = 1.790367, $p = 0.1212$): A marginally significant positive effect indicates that higher spending may raise interest rates, aligning with the crowding-out hypothesis where government borrowing increases demand for funds.

Tax Revenue (C(12) = -0.525563, $p = 0.0961$): A marginally significant negative effect suggests spending increases are financed through borrowing rather than immediate tax hikes.

Interest Rates Shock can be seen from the Table 3 also.

Tax Revenue (C(14) = -0.778217, $p = 0.0046$): A significant negative effect shows that higher interest rates reduce tax revenue by 0.78 units, likely due to slower economic activity or higher debt servicing costs reducing fiscal capacity.

The Tax Revenue Shock, as the last variable in the recursive order, it has no significant off-diagonal effects on others contemporaneously.

Regarding the key dynamic effects from accumulates IRFs from Table 4 we can econometrically interpret as follows.

Shock to GDP Growth (Shock1): Government Debt: A positive GDP shock reduces debt significantly in period 1 (-4.175249, SE=1.03243), but the effect weakens by period 5 (-3.734113, SE=9.86528), with large standard errors indicating statistical insignificance in later periods. The Tax Revenue increases persistently (0.912506 in period 1 to 1.273858 in period 5), with initial significance (SE=0.23526), suggesting a revenue-enhancing effect of growth. Interest Rates have minimal impact (-0.954378 by period 5, SE=7.27334), reflecting weak monetary spillovers.

Shock to Government Debt (Shock2): Interest Rates are being reduced consistently (-1.528623 in period 1 to -2.115685 in period 5), potentially signalling monetary easing, though standard errors grow (SE=6.23401 by period 5). GDP Growth has an initial positive response (1.104199, SE=1.02482) which fades to insignificance (0.454152, SE=5.92833), indicating limited feedback.

Shock to Government Spending (Shock3): The Interest Rates increase initially (0.382308, SE=0.64716), consistent with crowding-out, but the effect becomes insignificant (1.362553, SE=6.20153) by period 5. GDP Growth has an ambiguous effect, positive initially (0.315223) but negative by period 4 (-0.179047), with large standard errors (SE=6.92503 by period 5).

Shock to Interest Rates (Shock4): GDP Growth has a strong initial boost (3.851953, SE=0.76774), but reverses to negative (-0.898263) by period 2, suggesting a contractionary

effect over time. Regarding Tax Revenue we see a persistent decline (-0.455840 to -0.713285), aligning with reduced economic activity.

Shock to Tax Revenue (Shock5): GDP Growth has an initial negative impact (-1.732368, SE=0.29015), but becomes insignificant (0.552961, SE=6.42363) by period 5, indicating short-lived effects.

The results for Romania highlight GDP growth as a pivotal stabilizer: it reduces debt and spending while boosting revenue, reflecting its broad fiscal impact. Interest rate shocks have a contractionary fiscal effect, reducing tax revenue, while spending shocks tentatively support crowding-out. Debt shocks show limited immediate spillovers, suggesting slower fiscal-monetary transmission.

The small sample (18 observations) and crisis-heavy period (post-2008 and COVID-19) may amplify these effects, though larger standard errors (e.g., C(4), C(8)) reduce precision for some estimates.

These findings echo Bohn (1998) on the need for fiscal adjustment and highlight CEE-specific challenges noted by Mackiewicz-Lyziak (2015).

5. Conclusions

This study elucidates fiscal-monetary interactions shaping public debt dynamics in Romania (2005–2022) and the Czech Republic (1998–2022) using a Structural Vector Autoregression (SVAR) model. Contrary to expansionary debt growth, Romania's GDP growth significantly reduces debt (-3.474 contemporaneously, -4.175 dynamically), while the Czech Republic shows similar but less intense stabilization (-1.121). The SVAR framework, despite small sample constraints (18 and 25 observations), offers policymakers insights into balancing growth and sustainability. Future research could extend to other CEE countries or include variables like demographic trends.

For the Czech Republic, GDP growth significantly reduces government debt contemporaneously (-1.121, $p < 0.001$) and over time (-1.089 by period 5), underscoring its fiscal stabilizing role. Rising debt prompts immediate spending cuts (-0.670, $p = 0.0506$), but no significant interest rate increase, contrary to fiscal sustainability concerns. Government spending unexpectedly lowers interest rates (-0.716, $p < 0.001$) and GDP growth (-2.759 by period 5), suggesting monetary accommodation or model limitations. Interest rate and tax revenue shocks have limited impact, with the latter's negative effect on GDP (-1.118, $p = 0.1738$) requiring further scrutiny. These findings highlight growth's fiscal benefits and complex policy interplays, but recursive identification, small sample size, and anomalous IRFs necessitate caution.

For Romania, the SVAR analysis confirms GDP growth's pivotal role, significantly reducing debt (-3.474, $p < 0.001$) and spending (-1.626, $p < 0.001$) while boosting tax revenue (+1.160, $p = 0.0026$), consistent with economic theory. Interest rate shocks reduce revenue (-0.778, $p = 0.0046$), reflecting contractionary effects, while spending marginally raises interest rates (+1.790, $p = 0.1212$), supporting crowding-out. Significant coefficients

provide robust short-run evidence, though insignificant effects (e.g., growth on interest rates, -1.506 , $p = 0.2448$) suggest context-specific linkages, likely due to the crisis-heavy period or sample size. These results emphasize growth's fiscal benefits and policy interdependencies, contributing to stabilization debates.

Comparing Romania and the Czech Republic, both show GDP growth reducing debt, with Romania's effect stronger (-3.474 vs. -1.121) due to crisis dynamics (e.g., 2008, COVID-19). Romania's spending aligns with crowding-out ($+1.790$ on interest rates), unlike the Czech Republic's negative effect (-0.716), while Romania's positive revenue response to growth ($+1.160$) contrasts with the Czech Republic's insignificant negative effect (-1.118). Romania's shorter, volatile sample yields stronger fiscal effects but less precise long-term estimates (larger IRF standard errors), highlighting period sensitivity. Future analyses should test alternative identifications and larger datasets for robustness.

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Internal communication in public administration: a mechanism for institutional cohesion and a key driver of organizational performance

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Abstract. *Internal communication is fundamental to the cohesion and performance of public institutions. This paper explores how clear, consistent internal communication enhances organizational efficiency, supports decision-making processes, and fosters a transparent and accountable working environment. It highlights common communication challenges within public administration and argues for the need to professionalize internal communication practices to strengthen institutional effectiveness.*

Keywords: internal communication, public administration, organizational efficiency, institutional cohesion, transparency.

JEL Classification: D73, H83, M12, M14.

1. Introduction

If you work in public administration or are interested in organizational dynamics, this article provides practical tools and essential concepts to transform internal communication into a strategic asset. You will learn how to use the psychological influence of speech, effective language, and modern techniques to enhance team cohesion, decision clarity, and institutional performance.

In recent years, public administration in Romania, like other European countries, has faced a series of structural and functional transformations aimed at meeting the demands of contemporary society: administrative efficiency, digitalization, public accountability, and citizen orientation. In this dynamic context, internal communication has gained strategic importance, moving beyond its role as a mere vehicle for information transmission to become a key driver of organizational cohesion and institutional modernization.

Effective internal communication involves a bidirectional, continuous, and adaptable process through which an organization aligns its employees with its strategic objectives, fosters interdepartmental cooperation, prevents and manages conflicts, and contributes to building an organizational culture based on transparency, accountability, and active engagement. In this sense, communication not only supports the daily functioning of public institutions but also enhances their ability to address external challenges and generate public value.

Moreover, the efficiency of internal communication significantly impacts the motivation, job satisfaction, and loyalty of public servants, directly influencing institutional performance. Beyond technical and functional aspects, internal communication can also be analyzed from the perspective of behavioral influence, using psychosocial tools to promote cooperation, voluntary compliance with norms, and the adoption of organizational values.

Based on these premises, this paper aims to explore internal communication in public administration through the lens of social influence tools, with a focus on the applicability of Robert Cialdini's six fundamental principles: *reciprocity, commitment and consistency, social proof, authority, liking, and scarcity*. The analysis seeks to highlight how these principles can be integrated into the internal communication strategies of public institutions to enhance managerial efficiency, organizational cohesion, and collective responsibility.

Transforming internal communication within public administration can be significantly streamlined by strategically applying Robert Cialdini's six principles of social influence. These principles offer a psychosocial perspective on how behaviors and attitudes can be shaped ethically, transparently, and efficiently within public institutions.

2. Applying Cialdini's principles in public administration

Robert Cialdini is a renowned American psychologist known for his research on social influence and persuasion, synthesized in his seminal work *Influence: The Psychology of Persuasion*. His six principles of influence, reciprocity, commitment and consistency, social proof, authority, liking, and scarcity provide a robust scientific framework for understanding how behaviors can be shaped ethically and effectively within an organizational context.

In public administration, these principles can support the development of strategic internal communication that contributes to the coherence of institutional messages, employee motivation, strengthening organizational culture, and improving interdepartmental collaboration. When applied correctly, they become valuable tools for enhancing institutional cohesion and organizational efficiency in a sector often characterized by rigidity, bureaucracy, and resistance to change. As David Cowan notes in his 2023 book *Strategic Internal Communication: How to Build Employee Engagement and Performance*, “*Effective internal communication is not just about transmitting information but about creating a shared sense of purpose and fostering a culture where employees feel genuinely engaged and motivated to contribute to the organization’s success.*” (Cowan, 2023) This perspective underscores that, beyond the mere circulation of messages, internal communication plays a critical role in generating authentic engagement and building a robust organizational culture, both of which are indispensable in the dynamics of public administration.

2.1. The principle of reciprocity in institutional internal communication

The principle of reciprocity, a foundational element of social influence described by Robert Cialdini, reflects a deeply embedded social norm whereby individuals feel a moral and psychological obligation to return favors or support they have received. This tendency is so strong that, often, the reciprocation response may exceed the actual value of the received benefit, leading to disproportionate behaviors perceived as necessary from a relational and ethical standpoint.

In public administration, this principle manifests through the cultivation of an organizational climate based on recognition, support, and institutional generosity. When public servants feel respected, supported, and included through awards, honorary mentions, personalized feedback, or access to professional development opportunities, they are far more likely to respond with voluntary engagement, institutional loyalty, and proactive initiative in their daily tasks. Reciprocity thus becomes a mechanism for reinforcing institutional cohesion, with direct effects on organizational performance. As Jenni Field observes in *Influential Internal Communication*, “*An organization is not a real thing... for us to have influential internal communication, we have to understand people better,*” (Field, 2021) highlighting that internal communication is not only about message transmission but about understanding and valuing the people who make up the organization. In this sense, a culture of recognition and support becomes a relational infrastructure that fosters loyalty, meaning, and active engagement.

An advanced practice for ethically leveraging this principle is the institution of “institutional appreciation days,” where civil servants’ contributions are publicly acknowledged, or the implementation of a peer-to-peer digital feedback system, encouraging mutual recognition among colleagues. These initiatives boost internal motivation and strengthen the sense of belonging to an organization that values its human capital.

On the other hand, the principle of reciprocity can also be used strategically through specific conversational techniques, such as the “door-in-the-face” method. This technique

involves making an initially large request—likely to be declined—followed by a much more modest one, which, by comparison, seems reasonable and harder to refuse from a moral standpoint.

Example applicable in public administration:

A civil servant asks a colleague, “Could you cover the front desk until noon, please? I have a personal emergency.” The request is denied, as the colleague explains they already have scheduled commitments during that time. Later, the civil servant returns with a revised request: “I understand you're busy. Perhaps you could cover for just an hour, so I can quickly check my official correspondence?” The second request, using phrases such as “just,” “perhaps,” and “only,” which suggest modesty and limited effort, appears more reasonable compared to the initial one. The colleague may feel uncomfortable refusing again, motivated by the desire to maintain a positive image of collegiality and helpfulness.

This form of influence works not only due to the implicit comparison between the two requests but also because the requester shows understanding triggering in the recipient a need to be fair. In institutional environments where collaboration and mutual support are essential, this technique can be highly effective, provided it is not recognized and critically evaluated.

From this perspective, the psychosocial literacy of public servants becomes crucial. They must be trained not only in technical competencies but also in understanding these subtle mechanisms of influence. Reciprocity should be encouraged as a genuine institutional value, yet it must also be acknowledged as a potential source of relational pressure when excessively or strategically manipulated. As Mikael Krogerus states in *The Communication Book*, “*Do unto others as you would have them do unto you*” (Krogerus, 2018) a formula that transcends mere popular morality and signals a delicate balance: reciprocal gestures can build authentic alliances, but when instrumentalized, they risk creating tacit obligations and hidden tensions. In this regard, public institutions must cultivate reciprocity as an ethical practice while remaining vigilant toward subtle coercive dynamics that can undermine employee autonomy and freedom.

2.2. The principle of commitment and consistency in institutional internal communication

The principle of commitment and consistency, as defined by Robert Cialdini, reflects the deep-rooted tendency of individuals to act in accordance with prior commitments, especially when those commitments have been publicly expressed. From a psychosocial perspective, once a person has declared or demonstrated adherence to a particular action, idea, or value, an internal pressure is generated to maintain a coherent image both in the eyes of others and in one's own self-perception. This pressure persists even in situations where continuing the commitment no longer brings benefits or becomes disadvantageous.

In the context of public administration, this principle has major implications for internal communication and organizational culture. Civil servants who publicly assume roles, values, or objectives such as by participating in internal campaigns or formally taking on responsibilities are more likely to remain consistent with those commitments over time.

Thus, internal communication can incorporate mechanisms through which commitments are visibly expressed and recorded, contributing to the reinforcement of accountability and the continuity of desired organizational behaviors. As Kevin Ruck emphasizes in *Employee Engagement and Internal Communication*, “*transparency and clear articulation of commitments within organizations are fundamental to fostering accountability and sustaining desired behaviors over time.*” (Ruck, 2022). This perspective highlights the role of internal communication not merely as an information flow, but as a strategic tool for anchoring collective responsibility.

A clear illustration of this principle is the influence technique known as the “foot-in-the-door” strategy. This method involves starting with a minor, reasonable, and easily accepted request that paves the way for increasingly complex ones. For example, a new colleague may initially ask: “Could you show me how to submit a leave request in the electronic system?” a seemingly insignificant and non-disruptive inquiry. Later, the colleague may follow up with more elaborate requests such as: “Could you help me fill out the timesheet?” or “Would you mind reviewing this email before I send it to our supervisor?”, eventually progressing to more substantial requests like: “Could you take over my presentation on Friday? I have an emergency, and you’re already familiar with all the data.”

Each of these incremental requests may appear reasonable on its own, as each step is merely a slightly amplified extension of the previous one. However, the overall pattern can lead to an escalation that exceeds the comfort zone or the actual availability of the person being asked. In this context, Cialdini recommends assessing each request independently, rather than as part of a gradual process or a preexisting social relationship. It is important that public servants remain aware of this mechanism and retain the ability to refuse, with discernment, when requests surpass reasonable limits of their role or personal availability.

From an institutional communication standpoint, this principle also entails the ethical responsibility of leaders not to exploit employees’ prior commitments in a manipulative manner. Instead, it can be constructively employed to strengthen value alignment, voluntary engagement, and self-discipline among civil servants, by fostering an organizational climate that encourages responsible and transparent commitment-taking within a respectful and predictable framework. As Joanna Parsons notes in *Innovative Internal Communication: How Creativity, Curiosity and Technology Can Create Lasting Impact*, “*innovative internal communication is not just a message delivery channel, but a vital catalyst for building a trusting environment and genuine commitment,*” (Parson, 2024) thus underlining the importance of ethics and transparency in internal communication as a foundation for a sustainable organizational culture.

2.3. The principle of social proof in internal communication within public administration

The principle of social proof expresses the natural tendency of individuals to interpret the behavior of others as a valuable guide for their own decisions and actions especially in ambiguous, uncertain contexts or in the absence of a clear authority. This influence becomes particularly strong when the observer perceives a social or professional similarity with those whose behavior they are observing. In public administration a typically

bureaucratic, hierarchical, and formalized environment the behavior of experienced civil servants or the majority group often becomes an unofficial standard of conduct, even when it does not necessarily reflect explicit institutional norms. These tacit norms can have a powerful impact on organizational culture, either perpetuating practices that undermine institutional efficiency or reinforcing internal cohesion. As Mary Jo Hatch notes in *Organization Theory: Modern, Symbolic, and Postmodern Perspectives*, “*unofficial norms function as invisible threads that shape employee behavior, often becoming more influential than written regulations.*” (Hatch, 2024)

Therefore, in public administration, internal communication management must recognize and address these subtle realities, promoting open dialogue and critical awareness of informal practices in order to align implicit values with institutional goals and to foster positive change.

This principle can be used ethically and strategically to build a collaborative organizational culture when the examples being promoted align with the institution’s values and objectives. Sharing success stories of public servants, visibly displaying performance indicators, or formally recognizing outstanding contributions to public service can help shape internal behavior in a positive way. In this regard, initiatives such as the “Public Administration Heroes” campaign which highlights employees’ results through real and verifiable examples—can serve as effective tools for encouraging voluntary compliance and engagement.

However, this principle can also be manipulated if used to create social pressure or fabricate consensus that does not reflect reality. A common technique derived from this principle is manufactured consensus, in which someone claims that the majority of colleagues have already adopted a certain decision, in order to coerce others into conforming. For example, in an informal situation like organizing a year-end party or a retirement gift, a civil servant might say, “Everyone has agreed to contribute 200 lei each for Marius’s gift. So far, only you and two others haven’t paid.” In reality, the amount may have been decided by only two or three people, without true consultation of the team.

Recognizing this tactic is possible by paying attention to vague wording and generalizations: expressions like “everyone,” “all colleagues,” or “the majority” lack transparency and avoid identifying the real sources behind the supposed collective decision. In such cases, it is advisable to ask for specific, verifiable information: “Who exactly was consulted?”, “When was this amount decided?”, and, if needed, to confirm such statements independently with other colleagues. Refusing to participate in an arbitrary decision is not an act of isolation, but rather a legitimate form of critical thinking and individual responsibility.

Another example of strategically applying this principle might appear in a seemingly neutral request that subtly leverages social expectations, such as: “Good afternoon, I just have a quick question... Since you care about the quality of internal communication, would you be willing to complete the evaluation survey as well?” The phrasing exploits

universally accepted values, concern, responsibility, engagement and may exert implicit pressure on the employee to comply, even if they lack the time or real interest to participate. Such formulations should be assessed rationally, and one's response should not be dictated by the desire to conform to an idealized moral profile.

Therefore, the use of the principle of social proof in public administration must be balanced and transparent. On one hand, it can be a valuable ally in promoting ethical, responsible, and performance-oriented behavior. On the other hand, it is important that civil servants are trained to recognize indirect influence and develop a critical reflex to protect themselves from unfair group pressure or relational manipulation. As Liz Fosslien and Mollie West Duffy highlight in *No Hard Feelings: The Secret Power of Embracing Emotions at Work*, *“awareness of subtle social influences and the emotions accompanying them is essential to navigate organizational dynamics ethically and effectively, thus preventing passive conformity and manipulation.”* (Fosslien & Duffy, 2021) Accordingly, training civil servants in this area becomes a strategic step in strengthening autonomy and professional integrity within public administration.

2.4. The principle of authority in internal communication within public administration

The principle of authority becomes relevant when institutional leaders not only hold a formal position but also demonstrate expertise, clarity, and integrity essential elements in building trust and respect within the organization. In a public environment often characterized by complexity and rapid change, authentic authority is distinguished by leaders' ability to communicate transparently and coherently, offering employees not only directives but also explanations grounded in objective data and clear strategic visions. Effective communication thus becomes a vital tool for creating a climate of psychological safety, where civil servants feel supported and motivated to take on responsibilities.

Innovative practices such as “5 Minutes with the Director” are examples of modern communicative leadership, where short, consistent, and well-calibrated messages act as a bridge between leadership and employees, facilitating the flow of information and strengthening the sense of belonging. This strategy not only increases the visibility of leaders but also personalizes the institutional relationship, reducing hierarchical distance and fostering transparency.

As Kevin Ruck highlights in *Employee Engagement and Internal Communication*, *“authority is not merely a matter of hierarchical position, but is built through transparent and consistent communication that provides employees with clarity and a genuine sense of trust.”* (Ruck, 2022) In this context, leaders who invest in personalized, fact-based, and empathetic communication can transform formal authority into a true driver of engagement, responsibility, and institutional performance. This creates a virtuous circle where authority is reinforced through actions and dialogue, and communication becomes the foundational pillar of a healthy and dynamic organizational culture.

2.5. The principle of liking in internal communication

The principle of liking refers to people's tendency to be more receptive to those they find pleasant and who communicate empathetically. In public administration—often marked by

formal procedures and rigid hierarchical structures—creating an atmosphere of openness, respect, and emotional closeness is not optional, but a strategic necessity. Consciously cultivated institutional likability can reduce resistance to change, stimulate interdepartmental collaboration, and increase employee engagement.

Organizing informal events (e.g., “team breakfasts,” “guided conversation breaks”), adopting a warm and humanized tone in written or video messages, and promoting non-hierarchical dialogue all help to foster authentic interpersonal relationships and mutual trust. Likewise, encouraging sincere peer appreciation—whether through internal recognition platforms or simple verbal acknowledgments during meetings—contributes to team cohesion. One innovative technique in this regard is the creation of an internal podcast featuring employee participation, which offers an informal space for expression, promotes professional visibility, and builds cross-institutional empathy.

As Jenni Field states in *Influential Internal Communication*, “*employees don’t just respond to what is communicated, but even more to how it is communicated and the emotional connection created through language and behavior.*” (Field, 2021) Thus, internal communication based on likability becomes a catalyst for voluntary engagement and loyalty, particularly in the public sector, where organizational climate often suffers from excessive formalism and a lack of human connection in interactions.

2.6. The principle of scarcity in internal communication

Lastly, the principle of scarcity leverages people’s natural tendency to place greater value on what is perceived as exclusive, rare, or available for a limited time. In public administration—a field often dominated by routine and predictability—applying this principle in internal communication can serve as a catalyst for initiative and engagement.

Announcing professional development programs with limited spots, selecting participants for pilot initiatives addressed to specific groups, or promoting unique participation opportunities (e.g., “once a year only”) are all ways in which public organizations can spark interest and motivation among employees. Thematic campaigns—such as idea competitions, innovation scholarships, or annual recognition of outstanding contributions—can become strong symbolic milestones, adding value to professional commitment and giving visibility to individual initiatives.

As Nathalie Nahai points out in *Business Unusual*, “*the perception of scarcity triggers not only immediate response but also an association of value and importance with opportunities seen as rare or exclusive.*” (Nahai, 2022). When applied with discernment, this principle can help revitalize internal communication in the public sector, transforming limited access into a driver of attraction and active engagement.

By integrating these principles into a coherent internal communication strategy, public administration not only improves the efficiency of information dissemination but also builds a solid organizational framework where values, collaboration, and employee motivation contribute to the sustainable generation of public value.

3. Tactical Aspects of Internal Communication in Public Administration: From Influence to Organizational Cohesion

After consolidating the theoretical foundations of social influence through the principles formulated by Robert Cialdini, it is necessary to explore certain tactical dimensions of internal communication that support the influencing process in an ethical, strategic, and context-appropriate manner for the specific nature of public administration. These tactics do not aim to manipulate, but rather to optimize institutional dialogue, reduce resistance to change, and enhance the institutional capacity for adaptation and performance.

3.1. Conversational control

Conversational control involves a key competency of modern leadership — the ability to subtly and constructively guide the course of discussions, while avoiding explicit constraint or authoritarianism. This form of control is exercised through refined communication techniques such as the use of open-ended questions that stimulate reflection, active listening that validates expressed viewpoints, and reformulations that bring clarity and steer the conversation toward concrete, consensual solutions.

In the complex and often rigid environment of public administration, this skill becomes indispensable for effectively mediating interdepartmental conflicts, coordinating multidisciplinary teams, and facilitating the active and democratic participation of employees in decision-making processes.

A practical example is a department manager who facilitates a meeting without imposing pre-packaged solutions, instead encouraging dialogue with questions like: “What would be the most effective way to meet the deadline, considering the current resources?” This approach not only promotes accountability among participants but also fosters a collaborative, open, and respectful atmosphere.

As organizational communication specialist Kevin Ruck points out: “*Effective conversational control in leadership means creating an open framework where dialogue is oriented toward active listening and the pursuit of shared solutions, avoiding dominance or coercion.*” (Ruck, 2022)

This approach is particularly effective in building high-performing, cohesive teams especially in public administration, where complexity and the diversity of interests can generate tensions.

3.2. Framing and reframing situations

Framing is a fundamental concept in communication theory that refers to how information is structured and presented in order to shape perceptions and attitudes consciously or unconsciously. In internal communication, reframing becomes a strategic technique for redefining a situation or message, guiding its interpretation toward constructive, optimistic, or opportunity-oriented perspectives.

This approach not only reduces inherent resistance to change often amplified by institutional inertia and rigidity but also facilitates a culture of openness to innovation and adaptability.

Implementing reframing in public administration requires special attention to language and the meanings it activates among employees. For example, instead of saying “we’ll have to adapt our procedures again”, which may generate anxiety or perceptions of imposed effort, a reframed version would be: “This procedural adjustment gives us a chance to reduce bureaucracy and increase efficiency.”

This shift in discourse emphasizes the benefits of transformation, inviting increased receptiveness and voluntary engagement.

According to Tali Sharot, a specialist in decision neuroscience: “*The way information is framed directly influences how it is processed emotionally and cognitively, and reframing has the potential to transform a perceived threat into an attractive opportunity.*” (Sharot, 2020). This perspective confirms the importance of adopting calibrated internal messaging that supports change by promoting motivation and employee engagement.

3.3. Influence through language

Influencing through language is a fundamental instrument in internal communication because language not only transmits information but also structures perceptions and determines behavior within the organization.

In public administration where messages pass through complex hierarchies and must reach recipients with varied backgrounds and roles using precise vocabulary and an appropriate tone helps reduce misinterpretations and prevent internal conflicts. Clear expression facilitates a unified understanding of strategic directions and reinforces institutional cohesion.

Clearly articulating expectations and establishing firm deadlines supports collective accountability and reduces ambiguity. For instance, instead of vague phrases like “it may be implemented”, professional communication uses definitive statements such as: “Implementation will begin on June 15, in accordance with the approved strategic plan.”

This clarity directs actions and strengthens confidence in the decision-making process.

Michael Bungay Stanier emphasizes: “*Clear and intentional language is the key to building an organizational culture where people feel informed, respected, and empowered to act with confidence.*” (Stainer, 2020) This insight highlights the direct link between communication quality and institutional efficiency, especially in public structures where transparency and accountability are central values.

3.4. Subtle dialogue domination

Subtle domination of dialogue is a refined communication management technique that relies not on authoritative imposition, but on a balanced orchestration of conversational dynamics. It involves carefully controlling the pace of discussion, organizing messages in a clear and logical manner, and defining key argumentative points that serve as conceptual anchors for interlocutors.

In institutional environments, this approach helps maintain focus on the core objectives of the discussion, reducing the risk of unproductive detours or ambiguities that may cause confusion or decision-making bottlenecks.

As Judith Glaser observes “*An effective leader knows how to manage conversation in a way that allows all perspectives to be expressed, while still keeping the discussion aligned with the desired outcome.*” (Glaser, 2020). This technique offers space for input and diverse viewpoints, while the leader maintains the conversational framework to ensure coherence and alignment with organizational interests.

A practical application of this technique is the use of a clear communication structure such as “objective–problem–options–solution”, which ensures a logical, predictable flow of conversation and facilitates sound, consensus-based decisions.

3.5. Strategic Information Gathering

Strategic information gathering in public administration requires close attention to internal dynamics and a refined capacity to interpret both formal and informal feedback. This process ensures that messages are adjusted and decision-making processes optimized according to the organization’s real context.

Tools such as warm interviews, structured conversations, and thematic surveys are valuable methods for capturing not only expressed opinions but also subtle perceptions that shape behavior.

4. Techniques for relational calibration and large-scale influence

As Jennifer M. George and Gareth R. Jones write in *Understanding and Managing Organizational Behavior* “*Strategic listening and feedback interpretation are essential for building healthy organizational relationships and enabling deep change, as they allow leaders to navigate the complexity of human behavior with precision*” (George & Jones, 2021). Advanced dimensions of internal communication: nonverbal, emotional communication and scalable influence in public administration

In the context of deepening Cialdini’s social influence principles and conversational tactics, an often underestimated but critical area in public administration is nonverbal and emotional communication. These elements directly influence the efficiency of message transmission, organizational climate, and employee receptiveness to change.

Additionally, techniques for relational calibration and large-scale influence play a crucial role in reinforcing institutional cohesion and aligning internal communication with strategic objectives.

4.1. Nonverbal communication and emotion management

Nonverbal communication is not merely a complement to verbal discourse, but an autonomous form of transmitting affective and attitudinal information, with major impact on the perception of leadership and institutional credibility. In the context of public administration, where interactions are often formal, civil servants’ ability to decode body language, micro-expressions, and emotional tone becomes a strategic advantage.

Reading authentic reactions - Officials trained in decoding nonverbal communication can anticipate tensions, reluctance, or genuine support from colleagues, thereby contributing to the proactive adjustment of communication strategies.

Controlling personal expressiveness – Effective leaders rigorously manage their own body language; an open posture, balanced tone, and facial expressions congruent with the verbal message project calm authority and institutional stability.

Inducing positive emotions – Contextual storytelling, the use of inspirational examples, and a warm tone stimulate employees' emotional engagement, increasing attachment to institutional values.

Strategic neutrality – In crisis or conflict situations, adopting a calm, clear, and rational discourse, accompanied by neutral nonverbal language, helps stabilize the atmosphere and restore authority in dialogue.

Connection to the principle of authority: A leader perceived as calm, coherent, and controlled becomes a trust anchor during unstable times.

4.2. Rapport, calibration, and relational influence

In institutional communication, establishing effective rapport between interlocutors is fundamental for building a climate of trust and facilitating collaboration. This relationship is built through subtle and precise techniques of behavioral and emotional alignment, borrowed from the psychology of influence and persuasive communication.

Instant rapport is created through genuine eye contact, moderate postural mirroring, and expressed empathy, stimulating interpersonal connection and openness to dialogue.

Mirroring techniques – Subtle reflection of gestures, tone, or speech rhythm generates psychological resonance and a sense of synchrony, favorable to message acceptance.

Advanced calibration involves continuous adaptation of communication content and form based on nonverbal cues and recipients' reactions. This ability becomes vital during interdepartmental interactions or organizational conflict mediation.

Link to the principle of liking: People who reflect and understand others' emotions are perceived as more agreeable, which amplifies influence effectiveness.

4.3. Large-Scale Influence and Communicational Coherence

In public institutions, effective influence is not limited to interpersonal dialogues, but also manifests at the macro level through official internal communications that shape organizational culture. This influence is built through:

- Repetition of key messages, reinforcing the internalization of institutional values and goals;
- Appeals to shared values, which activate a sense of belonging and legitimize strategic directions;
- Stylistic consistency, which creates a clear and predictable identity framework in communication.

Reflection of the commitment and consistency principle: The coherence of institutional messages over time leads to behavioral alignment and employees' loyalty to the institution's mission.

4.4. Critical thinking and informational discernment

In an organizational climate marked by informational volatility and external pressures, rigorous source verification, logical content analysis, and critical thinking become essential competencies for public servants. Internal communication must not become a channel for spreading uncertainty or misinformation, but a stronghold of institutional rigor.

Assessing real vs. false information is a critical practice to avoid decision-making errors and to strengthen a culture based on integrity and professionalism.

Connection to the principle of social proof: In the absence of critical frameworks, people tend to believe and follow what “the majority accepts,” reinforcing the need for leadership that guides the information-filtering process.

Tactical integration: from interpersonal communication to institutional influence

Nonverbal, emotional, and contextually calibrated communication does not operate in isolation, but integrates with conversational tactics such as subtle dialogue control, managing the rhythm and tone of conversations, and advanced verbal persuasion techniques previously described. These tools, together with Cialdini’s principles (reciprocity, commitment, authority, liking, social proof, scarcity), provide a coherent operational framework for building influential, coherent, and people-centered institutional communication.

5. Conclusion

When approached as a strategic and professionalized function, internal communication transcends its traditional operational role and becomes a key vector for the modernization of public administration. The deliberate integration of social influence principles into the architecture of institutional communication not only optimizes information flow but also shapes organizational attitudes, behaviors, and values.

In this framework, communication is no longer a simple transmission tool, but a mechanism for cohesion, accountability, and systemic adaptation. A public administration that values internal communication as a pillar of internal governance succeeds in building a resilient organizational culture based on transparency, engagement, and value congruence. In an increasingly complex and volatile administrative context, the ability of institutions to remain agile, responsive, and citizen-centered depends significantly on the quality of internal dialogue. Therefore, investment in internal communication is not merely a technical or symbolic act, but a structural condition for organizational efficiency, legitimacy, and sustainability.

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Navigating the digital tide: how technology reshapes public policies and labor market across Europe

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Abstract. *This study investigates the impact of digitalization on public policy formulation and implementation within the European Union (EU). The research aims to elucidate how digital transformation influences policy effectiveness, citizen engagement, and administrative efficiency. Employing a mixed-methods approach, the study integrates quantitative data analysis with qualitative case studies. Quantitatively, data from EU member states were analyzed to assess correlations between digital adoption metrics and policy outcomes. Qualitatively, case studies from select countries provided in-depth insights into the mechanisms through which digital tools affect policy processes. Findings indicate that higher levels of digitalisation are associated with improved policy responsiveness and increased public participation. Moreover, the study also identifies significant challenges, including digital divides that may exacerbate existing inequalities and the need for substantial investments in digital infrastructure and skills development. The research concludes that while digitalisation offers substantial benefits for public policy, careful consideration of its limitations is essential. Future policies should address these challenges by promoting inclusive digital strategies and ensuring that technological advancement do not leave segments of the population behind. Limitations of the study include potential biases in self-reported data and the rapidly evolving nature of digital technologies, which may outpace current policy framework. Further research is recommended to explore long-term impacts of digitalisation on governance and to develop adaptive policies that can keep pace with technological change.*

Keywords: digitalisation, public policies, labor market, discriminant analysis, technological integration.

JEL Classification: O33, O38, J24, C38, H11, E24, L86.

1. Introduction

Globally, the digital economy has become a key driver of economic growth in the last decade, being defined by the International Telecommunication Union as the totality of economic activities facilitated by digital technologies. The rapid progress of these technologies (such as cloud-computing, big data, artificial intelligence and the Internet of Things) has produced profound transformations, restructured traditional industries and generated entirely new markets and business models. This digital transformation is manifesting itself in both the private and public sectors (Girardi et al., 2024). Private organizations are reconfiguring their processes and business models by integrating new technologies, while the public sector is moving towards e-government, digitizing administrative services and procedures for increased efficiency and accessibility. The literature has extensively examined these phenomena: a recent systemic analysis shows that, in the case of the public sector, studies have focused on defining the concepts of digitalization, on the advantages of e-government strategies and the conditions for their success, as well as on the determinants and impact of the implementation of technology in administration. However, studies in the same area highlight notable technological and empirical gaps, emphasizing that political science can further contribute to understanding the variety of contemporary strategies by justifying the need to expand research in the field, especially in order to fully capture technological integration in public and private structures (Bousrih et al., 2022).

The impact of digitalisation on the labor market is an intensely debated topic. On the one hand, classical economic theories suggest that technological progress boosts productivity and, in the long run, creates new job opportunities, indeed, in the past every wave of innovation (such as, for example, in the recent past, the automation of office tasks) has been accompanied by the emergence of new jobs that have compensated for the losses, maintaining the net positive effect on employment (Li et al., 2024). On the other hand, however, recent literature points out that the current digital revolution has distinct characteristics: advanced automation and artificial intelligence can replace not only repetitive manual work, but also complex cognitive tasks, which calls into question the economy's ability to absorb the freed labor force (Al-Zoubi, 2024). A novel element of this technological transformation is the fact that algorithms and software robots can take over intellectual activities once reserved for humans, for example the automated generation of news or reports, demonstrating that intellect-based work has also become susceptible to automation (Ding et al., 2021).

The consequence anticipated in the literature is a significant structural readjustment of the labor market: digitalisation simultaneously creates efficiencies and new professional roles, but also eliminates jobs in sectors or employment, potentially accentuating the polarization of skills and inequalities between different categories of workers. In this context, many authors stress the importance of reskilling and the continuous development of the digital skills of the workforce, in order to prevent the increase in structural unemployment and ensure the compatibility of available skills with the requirements of new technologies (Cursoe et al., 2024). In other words, human capital must be adapted to the digital transition, with education and training becoming central levers through which society can transform technological potential into inclusive socio-economic benefits. The present paper, thus,

represents an overview of these issues and the identification of discrepancies that occur in the member countries of the European Union. In the analysis of this paper we have separated the countries according to the scores obtained based on the representative indicators described in the methodology section. Highlighting differences is an important central point in establishing effective and documented public policies.

2. Literature Review

Given these transformations, public policies play a key role in facilitating the digital transaction and mitigating its adverse effects. The literature highlights the need for governments to create a framework conducive to large-scale digital technology adoption, concomitantly with digital inclusion measures. Among the priorities identified are reducing the educational gap in the digital field (through investments in education and programming to increase digital skills among the population) and encouraging companies, especially SMEs, to integrate advanced digital tools, by supporting IT investments and developing appropriate skills among employees (Bousrih et al., 2022). Such measurements can amplify the diffusion of technological innovations and enhance modernization: the adoption of digital defunctionalized principles "digital by design", the design of public services from the very beginning in digital format, centered on the needs of users, is considered a key factor for improving administrative effectiveness and stimulating citizens' participation in the act of government (MacLean & Titah, 2022). In parallel, public policies must strengthen trust in the digital environment by ensuring cybersecurity, data protection and educating users in online risk management, these elements being essential for the benefits of the digital transformation to be fully exploited by all socio-economic actors (Haug et al., 2024). Last but not least, government policies have a responsibility to ensure that the digital transformation is inclusive and does not exacerbate existing divides.

The concept of the digital divide takes on particular importance in this context. Digital inequalities refer to disparities in access to information and communication technologies, in the way they are used and in the benefits obtained by different population groups. These disparities often reflect pre-existing socio-economic inequalities in society, which is why reducing them is considered crucial for the sustainable development of a digitalized society (Yang et al., 2024). The digital divide therefore encompasses inequality between individuals, households, organizations or geographical areas in terms of access to and use of geographical resources (Viswanathan et al., 2022).

If active public policies for digital inclusion are not implemented, there is a risk that digitalisation will deepen these divides: people and communities that do not have access to quality infrastructure or strong digital skills can be left behind as the economy and administration become increasingly digital, ending up feeling partially or totally excluded from society (Zhang et al., 2022). Such observations have led to the intensification of public policy efforts aimed at expanding digital infrastructure and programming to increase digital inclusion, in order to ensure that the benefits of the digital economy are distributed as equitably as possible. Reducing digital gaps is not only a matter of social justice, but also a condition for maximizing the innovative and productive potential of digitalization at national level.

The dominant directions in the literature therefore outline a mixed theoretical framework: on the one hand, the focus is on the transformative potential of the digitalisation of the economy, growth stimulation, innovation in the public and private sectors, sports efficiency of services, and on the other hand, the associated risks and challenges, labor market disruptions, new skills requirements, as well as the risk of increasing digital inequalities are highlighted. At the same time, the literature also points out notable gaps that require further investigation. For example, in the sphere of digital governance, the subject of the diversity of digitization strategies and their comparative impact on institutions and societies has not been exhausted, which indicates the need for further research on this topic (Vial, 2021).

At the same time, studies are needed to critically assess the effectiveness of public interventions in bridging the digital divide and examining the extent to which they succeed in generating sustainable socio-economic outcomes, linking the objectives of digital transformation with those of sustainable development (Twizeyimana & Andersson, 2019). In this context, the present paper aims to contribute to the existing literature by integrating the mentioned themes, economic digitalization, labor market and public policies, and by providing new empirical evidence. By investigating the interdependencies between the adoption of digital technology, changes in occupational structure and public policy initiatives, the state of the art partially fills the gaps identified in the literature. Thus, its original contribution consists in nuancing the theoretical framework of digital transformation and providing useful scientific support to decision-makers, in order to formulate informed policies that maximize the benefits of digitization and reduce digital inequalities.

3. Methodology

The data used for the analysis in question were taken and modeled from the Eurostat database, for the period 2021 – 2024. Among the variables included are Integration of internal processes (integration), Percentage of The ICT sector personnel in total employment (perc_ict_emp), Percentage of the ICT sector in Gross Value Added (perc_ict_gva), Human Resource in Service and Technology domain – in tech employee (hrst), Enterprises that employ ICT specialists (emp_ict), Enterprises that tried to recruit ICT specialists (recruit_attempt) and Employment in technology and knowledge-intensive sectors (emp_tech). These variables were chosen because they provide a complex overview of how countries position themselves in terms of technology adoption and adapting the workforce to new technological requirements.

In the pre-processing stage, the data were first checked to facilitate references within the R code, using short names that can be seen in parentheses, next to the name of the indicators, immediately after their description in the paragraph above. Naming was essential to simplify data handling and avoid errors related to spaces or special characters in variable names.

The first step in data processing was the standardization of data usage. Considering that variables were measured in different units and that their ranges can vary significantly, we

applied a transformation by which each variable was brought to a mean of 0 and to a standard deviation of 1, using the `scale()` function in R. Both the tables with descriptive statistics of the data both standardized and before they were taken, can be analyzed in the Appendix of the paper, respectively in Table A1 and Table A2. To highlight inter country differences, we created a grouping variable based on the indicator 'Enterprises that tried to recruit ICT specialist'.

The choice of this indicator was justified by the fact that it represents the recruitment effort in the IT sector, a critical aspect in assessing the adoption of technology and the integration of new work processes, including Artificial Intelligence, IoT and other technologies that require companies to hire specialists in order to be able to cope with new work processes. The values of this indicator were divided into five categories: Very Low, Low, Medium, High, Very High, using thresholds defined by quantifiable – thus the distribution of observations was balanced, each category having an approximately equal number of observations.

The division method not only allows an analysis of the variables themselves, but also a comparison of countries according to the level of recruitment effort, providing a clear and well-defined segmentation. To exploit the differences between groups and to understand how the indicators vary between categories, we applied linear discriminant analysis (LDA). The choice was based on the ability to reduce the dimensionality of data by synthesizing information from multiple predictors into a smaller number of discriminating functions, as well as to classify observations according to defined groups. The LDA model was built using the formula that includes all standardized variables as predictors and the grouping variable as the dependent variable. The results include the a priori level of probability which shows the initial level of probability (about 20% for each category, due to the balanced division), the "Group means" from which it is possible to observe the average values of each indicator in each group, as well as the "Coefficients of linear discriminants" which highlight the significant contribution of each predictor to the discriminant functions.

To evaluate the model's performance, we used the confusion matrix that compared the actual labels of the observations with those predicted by the model, providing a quantifiable measure of the accuracy of the classification. At the same time, we performed a cross-validation (Leave-One-Out Validation) to test the robustness of the model and check for any overfitting problems. The two metrics provide pertinent information to observe how correct the model was in making predictions.

In the final stage of the analysis we generated a series of graphical representations to illustrate how groups separate in the space of discriminant functions. These visualizations were generated in RStudio, the same dedicated econometrics software, and are essential to communicate the results of the analysis in a simplistic way. The methodology adopted in the paper coherently integrates the preprocessing of data, the creation of a balanced and justified grouping variable (based on a critical indicator), the allocation of linear discriminant analysis to reduce dimensionality and classify information.

4. Results

The analyzed data were calculated and graphed for a better understanding. This section will detail, using the methods described above, the fact that the member countries of the European Union are distinctly placed from an evolutionary perspective. The need to outline these differences only draws clear differences in the different efficiency of economic incentives with regard to technological development as a whole.

Table 1 – Group Variables Quartiles illustrates how we have segmented countries according to recruitment efforts in the IT sector, a key indicator for assessing technology adoption in the current economic context. More simply, to reflect the differences in the technological approach of the countries, we divided the values of the indicator "Enterprise hat tried to recruit IT specialists: into five categories, using quantiles. This method has resulted in cynical intervals as can be seen below. Thus, each country is classified according to the relative position of its recruitment effort, which allows for a balanced and economically relevant comparison.

Table 1. *Group Variables Quartiles. Creating the group variable*

Category Name	Very Low	Low	Medium	High	Very High
Quantile Breaks	0% - 20%	21% - 40%	41% - 60%	61% - 80%	81% - 100%
No. of Obs. Outcome	56	57	55	56	56

Source: Authors own processing of data using RStudio (v 4.4.2).

From an economic point of view, such an approach is very useful because it allows for the formulation of tailored public policies. For example, the countries of the "Very Low" group may require interventions and investments to stimulate modernization and technological adoption, while the countries of the "Very High" group can be studied as models of good practice for efficiency and innovation. The results show that the number of observations in each category is almost equal (Very Low – 56 observations, Low – 57 observations, Medium – 55 observations, High – 56 observations and Very High – 56 observations), which means that the split method managed to ensure a balanced distribution. This balance is crucial for subsequent analyses, as it allows for clear performance comparisons and the identification of significant differences between segments. Based on this analysis, a point table was generated with each country and when, depending on the query, it occupied a certain place in the ranking of the five groups. By adding it into columns, the number of data for each of the cynical categories will be observed. For each individual analysis, it is recommended to treat individually, at the national economic level, in order to identify discrepancies, if they exist. The values can be seen in Table A3 in the Appendix.

Subsequently, in order to observe the differences between the analyzed groups, **Table 2 - Group Means for LDA Analysis with 5 categories** was generated, for each of the five groups. The table is fundamental because it summarizes the average differences between country segments, providing a clear insight into how the technological characteristics differ according to the recruitment effort of ICT specialists. The "Very Low" category records negative average values for all indicators, such as internal process integration, share of ICT staff, contribution to gross value added, human resources in technology and the rest, which indicates a lower level of technological development. In contrast, the "Very High" group shows significant positive average values, suggesting a more advanced adoption and

implementation of technologies. The average values of the intermediate groups (Low, Medium and High) fall between these extremes, illustrating a gradual shift in the level of digitalisation.

Table 2. *Group Means for LDA Analysis with 5 categories*

	integration	perc_ict_emp	perc_ict_gva	hrst	emp_ict	emp_tech
Very Low	-0.57489999	-0.75869387	-0.7308265	-0.7416715	-0.43499681	-0.9095596
Low	-0.30027693	-0.37983911	-0.3987671	-0.5009867	-0.50785528	-0.3723967
Medium	-0.09891448	0.08862242	0.2217137	0.1869982	-0.01037369	0.1801096
High	0.21914661	0.33124038	0.3496640	0.2901767	0.27371022	0.5864266
Very High	0.75854054	0.72703556	0.5692960	0.7777687	0.68839917	0.5252863

Source: Authors own processing of data using RStudio (v 4.4.2).

The presentation of the averages by group allows the identification of indicators that have a major influence on the differentiation between segments, thus facilitating the interpretation of the digitization structure of countries. For example, the marked difference between the average of the integration indicator in the 'Very Low' and 'Very High' groups underlines the importance of this factor in determining the degree of technological adoption. In the context of public policy-making, these results can guide the formulation of tailored strategies: countries in the lower segments can benefit from specific interventions for modernization, while countries in the upper segments can serve as models of good practice.

The Table of Importance and the coefficients of discrimination functions that can be calculated in **Table 3** provide a rough insight into how each indicator contributes to the differentiation of countries according to ICT recruitment efforts. Essentially, each discriminant function (LDA1, LDA2, LDA3, LDA4) is derived as a linear combination of predictor variables (indicators). The coefficients associated with each predictor in these functions indicate the relative weight or impact that each indicator has in the separation of the groups.

Table 3. *Coefficients (Coef) of linear discriminants & Importance (Imp) Table*

	LDA 1		LDA 2		LDA 3		LDA 4	
	Coef.	Imp.	Coef.	Imp.	Coef.	Imp.	Coef.	Imp.
integration	-0.651117	29.1	0.237468878	6.3	0.3573244	6.3	0.3965378	13.3
perc_ict_emp	-0.063953	2.9	1.048262700	27.8	1.6862609	29.8	0.1750218	5.9
perc_ict_gva	-0.437660	19.6	-0.56925265	15.1	-1.811912	32.1	0.7365711	24.8
hrst	-0.539001	24.1	-0.00769024	0.2	-0.835427	14.8	0.1641452	5.5
emp_ict	-0.263168	11.8	0.679300891	18.0	-0.236219	4.2	-0.914116	30.8
emp_tech	-0.282790	12.6	1.235324221	32.7	0.7231209	12.8	-0.584343	19.7

Source: Authors own processing of data using RStudio (v 4.4.2).

The values of the coefficients in each discriminant function indicate how the variant of a particular indicator influences the separation between groups. For example, in the first discriminated function (LDA1), the coefficient for the "integration" indicator is -0.6511, with a relative importance of 29.1%. This information suggests that, from an economic point of view, the degree of integration of domestic processes has a major influence in the differentiation of countries. Thus, countries that demonstrate a high integration of domestic processes, reflected by positive and significant values in LD1, tend to have a better capacity to adopt modern technologies, which translates into a sports economic completeness on the

global market. In the contract, the "perc_ict_emo" indicator shows a very low coefficient of -0.06395, with an importance of only 2.9%, which indicates that, in the context of this analysis, the share of ICT personnel does not have a significant impact on countries. The discrepancy suggests that not all aspects of the ICT sector have the same role in driving technology adoption and involvement in economic growth.

The analysis of relative importance, calculated by relating the absolute value of each coefficient to the total sum of the absolute values of the same discriminant function, provides a clear measure of the influence of each indicator. In LDA 1, indicators with high importance (such as "integration", "hrst" and "perc_ict_gva") become the main object of the analysis, suggesting that improvements in these aspects could lead to significant economic benefits at some point. For example, an increase in the integration of internal processes can lead to a more efficient use of resources and a reduction in operational costs, which are critical for the long-term competitiveness of modern economies. Moreover, by analyzing the subsequent discrimination functions (i.e. LDA2, LDA 3 and LDA 4 analyses), it can be seen that there is a multidimensional structure of the data, in which each function captures a different part than the existing total variation. Although LDA 1 accounts for the largest share of differentiation (i.e. around 89% of the total variation), the other functions offer additional information that may be relevant for a more detailed analysis of segmentation between countries. In the representative economic context, these variations can ensure that, in addition to the main factors such as integration, there are other secondary factors, such as the percentage of ICT staff or investment in technology, which contribute to the positioning of countries, but to a somewhat lesser extent. **Table 4** thus serves as a map of the determinants of technological competitiveness. He highlights which issues must be addressed as a priority through public policies. A good illustration of how these elements can lead to much more complete information of public policy makers in the field is to improve the integration of internal processes or the development of human resources in the technological field, in order to stimulate technological adoption and, consequently, economic growth. Such results are not only statistical, but also provide concrete directions for strategic interventions in public policy, fundamental to the empirical differences observed between groups.

The distribution of the variation explained by each discriminant function highlights the central role of the first component (LDA 1) in separating the groups defined in the analysis. According to the values obtained, DLA 1 concentrates 89.19% of the total variation between groups, which indicates a high ability to differentiate observations based on the linear-weighted combination of technological indicators. The following functions, LDA 2, LDA 3 and LDA 4, contribute to a much smaller extent, explaining 7.32%, 2.67% and 0.75% of the variation, respectively. This distribution of information suggests that structural differences between countries in terms of the level of technological integration and the digitization effort are almost entirely reflected by its first discriminator. Consequently, economic interpretations and the development of public policy directions can be fundamental primarily on the variables that dominate LDA 1, as they concentrate the critical factors responsible for the polarization of performance between the analyzed segments.

Table 4. *Proportion of Trace*

LDA 1	LDA 2	LDA 3	LDA 4
0.8919	0.0739	0.0267	0.0075

Source: Authors own processing of data using RStudio (v 4.4.2).

From an economic perspective, DLA 1 reflects a main direction of variation between countries depending on the degree of digital development and technological integration, aggregating the effects of the indicators considered. The fact that LDA 2, LDA 3 and LDA 4 make marginal contributions suggests that the variables that contribute mainly to these functions do not have a decisive structural role in the delimitation of groups, but rather provide additional details. That structure is characteristic of situations in which a narrow set of explanatory factors concentrates the major differences in economic or institutional performance between the entities analyzed. Therefore, empirical interpretations and public policy recommendations can be justifiably centered on the dominant variables in DLA 1. This pronounced concentration of relevant information in the first discriminating function highlights not only the effectiveness of the LDA model in capturing technological disparities between countries, but also its potential for applicability in benchmarking digital performance. In this context, practical testing of the model's ability to distinguish observations in predetermined groups becomes essential. To support these conclusions and verify the robustness of the model, it is necessary to analyze the classification results generated, comparing the predicted values with the actual ones through a standard tool: the confusion matrix.

The confusion matrix shows the model's ability to correctly classify observations (in this case countries and years) into the five defined groupings, depending on the technology aggregate sector derived from the standardized variables (e.g., integration, share of ICT in GVA, employment in technical sectors, and so on). The table structure allows you to identify the performance of diagonal classifications (correct predictions) and classification errors (values outside the diagonal). The matrix pattern in **Table 5** shows high performance in recognizing extreme categories. For example, 42 of the 56 observations in the 'Very Low' group were correctly classified, and for the 'Very High' group, 39 out of 56 observations were accurately identified. This confirms that LDA 1, which accounts for 89.19% of the variation between groups, is able to capture the stark contrasts between countries at the poles of the technological transition. On the other hand, observations in the intermediate categories (Medium, Low and High) are more susceptible to classification errors. Only 21 out of 55 observations in the Medium category were correctly framed, while 13 were mistaken for High and 8 for Low. These results reflect a natural overlap of the economic-technological characteristics in the middle area of the distribution, a phenomenon frequently encountered in economies in the digital transition where the differences in technological capacity are more subtle.

Table 5. *Confusion Matrix*

		Predicted					
		Very Low	Low	Medium	High	Very High	Total
Actual	Very Low	42	9	3	1	1	56
	Low	20	29	3	4	1	57
	Medium	6	8	21	13	7	55
	High	4	7	13	21	11	56
	Very High	1	2	6	8	39	56

Source: Authors own processing of data using RStudio (v 4.4.2).

From an economic and public policy point of view, this classification structure suggests that the clearest and most effective interventions can be directed to extreme groups, where models precisely distinguish behaviors and needs. For intermediate groups, policy strategies need to be more refined and adaptive, taking into account the uncertainty of classification and the complexity of the digital transition. In order to increase the accuracy of the analysis and at the same time to draw clear directions regarding the values that can be used in the public policy plans, the matrix for evaluating the accuracy and generalization of the model was also developed. Thus, the "Leave-One-Out" validation, the essential technique for testing the stability of the model outside the antenna sample, was generated and can be consulted in Table 6. In this procedure, each observation is classified using a model built without that observation, which provides a rigorous measure of the ability to generalize. The results rate a high consistency between the original classification and the one obtained by validation, which supports the robustness of the estimate. In the Very Low group, a high level of accuracy is maintained (41 out of 56 classified corrected observations). The results validate that the model is not overfitted (the phenomenon of overfitted is not presented) and retains its discriminatory power when applied to new data.

Table 6. *Leave – One – Out Validation*

		Predicted					
		Very Low	Low	Medium	High	Very Vigh	Total
Actual	Very Low	41	10	3	1	1	56
	Low	20	28	4	4	1	57
	Medium	7	9	18	14	7	55
	High	5	6	13	17	15	56
	Very High	1	2	3	12	35	53

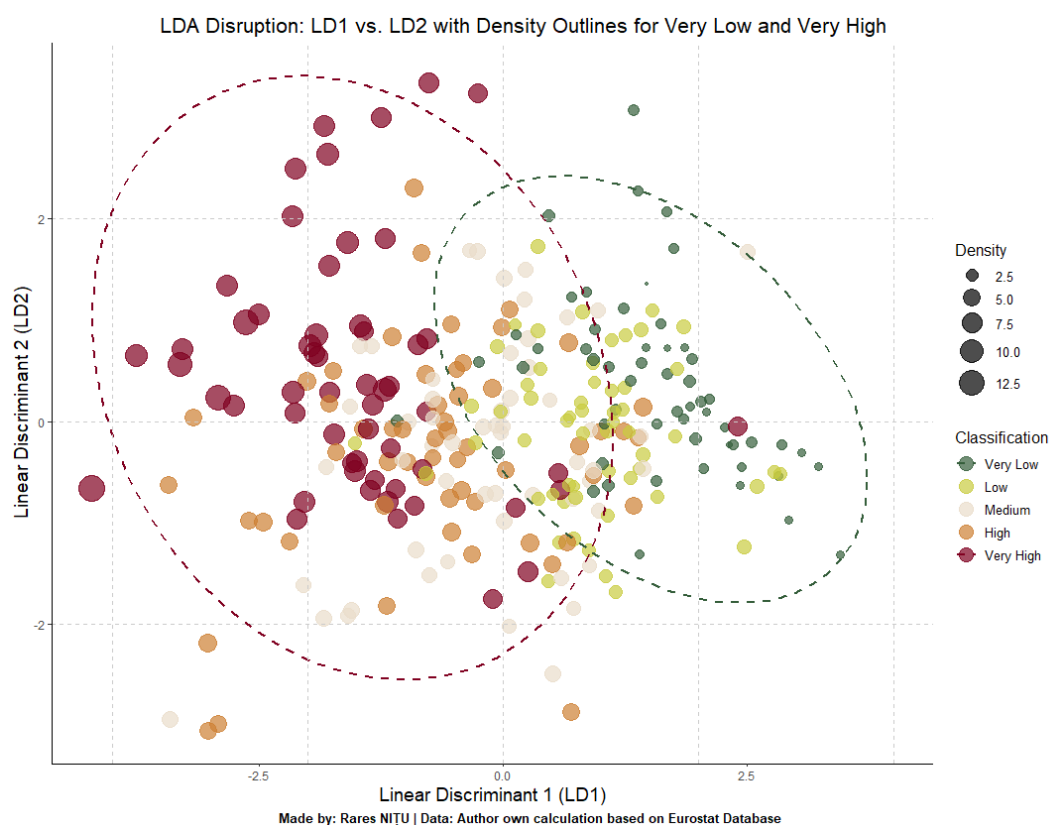
Source: Authors own processing of data using RStudio (v 4.4.2).

The slight decrease in performance for the Medium and High categories is expected and can be attributed on the one hand to the overlap of traits between these groups, and on the other hand, to the limited nature of the structural differences between countries on the verge of digital transformation. In this context, the results confirm that the model is sensitive to real developmental gradations and does not produce artificial distortions. Together, the two tables support the idea that the LDA model applied is valid, stable and useful for interpreting the differences in digital development between European countries, based on a set of relevant structural indicators. Its ability to accurately distinguish the extreme categories offers a valuable tool for formulating different public policies, while the errors in the middle area accurately reflect the real degree of uncertainty and complexity encountered in the comparative analysis of technological development. Thus, statistical interpretations serve as a solid fundamental basis for assessing the digital maturity and responsiveness of states in the context of the transformation generated by new technologies.

In order to visually support the conclusions of linear discriminant analysis and to highlight how the functions extracted by the model manage to separate the observations into the defined categories, a series of graphical representations in the discriminant space were generated. These graphs illustrate the distribution of observations according to the scores obtained on the first two (or more) discriminant functions, in particular LDA 1 and LDA 2, which concentrate most of the relevant information on the variation between groups. The main graph, made in two-dimensional space (LDA 1 and LDA 2) serves as an intuitive tool

for observing the structural differences between the "Very Low" and "Very High" categories, outlined by density ellipses. The presence of compact agglomerations of points within these contours suggests the existence of common features within each category, while the degree of overlap between the groups reflects the level of separation (or confusion) between them. The size and transparency of the points render the relative intensity of the indicator used for grouping (ICT recruitment attempts), adding an additional layer of interpretation on the intensity of the analyzed phenomenon. This visual approach therefore allows not only the validation of the numerical results obtained in the confusion matrix, but also the identification of spatial distribution models that can guide economic interpretations and the formulation of policy recommendations. The graphs constitute an essential bridge between formal statistical analysis and the applicable understanding of the differences between European countries in terms of the level of digital integration and the ability to adapt to the technological transition.

Figure 1. LDA Disruption: LDA 1 vs LDA 2



Source: Authors own processing of data using RStudio (v 4.4.2).

Figure 1 presented visually illustrates the results of linear discriminant analysis (LDA), focusing on the first two discriminant functions, LDA 1 and LDA 2. The graph provides an intuitive and clear representation of the pattern in which the analyzed countries are distributed in the space defined by these two axes, each point corresponding to a country

in a given year and being classified according to the level of the score obtained based on the discrimination function formed by combining the individually collected and correlated indicators.

The first discriminant function (LDA 1), represented on the horizontal axis, explains most of the variation between the analyzed groups (98.19%), which reflects the dominant role of this function in differentiating countries based on technological capability and digital integration. LDA 2 illustrates on the vertical axis, contributes to a lesser extent to differentiation (7.39%), but adds an additional layer of detail that allows a better identification of nuances in the behavior of countries. The "Very High" and "Very Low" categories are highlighted by distinct ellipses, emphasizing the relatively clear grouping of countries with extreme technology performance.

The ellipsis of the "Very High" category (dark red) illustrates countries with a high capacity for digital integration and with an increased intensity of recruitment efforts, characteristic of advanced digital economies. Correspondingly, the "Very Low" ellipsis groups countries that face major challenges in attracting technology specialists, reflecting a low capacity for technological integration and implying risks of marginalizing the digital economy. The dots in the graph have different sizes, corresponding to the intensities of the measured phenomenon.

Thus, the larger points indicate countries and periods with considerable efforts in attracting specialists, these being predominantly concerted in the "Very High" ellipse. The distribution of points thus confirms a direct relationship between the level of recruitment efforts and the overall digital integration of the national economy. The overlapping of points between intermediate categories (Low, Medium and High) suggests the existence of a common area, where the differences between countries are not so obvious and where the digital transition is still ongoing, without a particular category dominating decisively.

This overlap reflects the economic and technological complexity in the middle area of the digital transition and underlines the fact that countries in this category require specific policies, personality, in order to clearly progress towards the upper segment of technological integration. Countries with high frequencies in the upper categories of distribution, such as Belgium, Luxembourg, Malta, the Netherlands, Denmark and Sweden, point to an accelerated structural adaptation to the European digital economy.

The economies described are distinguished by an ecosystem of advanced innovation, public policies favorable to digitalisation, labor markets well calibrated to absorb the highly skilled workforce and a pronounced economic dependence on sectors with high added value. The number of years in which these countries are in the "Very High" category reflects a consolidated economic profile around technology, but also an institutional capacity to support continuous training in STEM fields and to stimulate aggregate demand for IT specialists to help companies operate the new technologies they need to cope with high competitiveness. The specific features support stable macroeconomic performance and competitive positioning in global value chains.

In contrast, economies such as Romania, Bulgaria, Poland, Italy, Latvia and Greece show a preponderant concentration in the "Very Low" and "Low" categories, which indicates a

persistent gap in terms of technology integration in productive sectors. The low frequency of research and development staffing, the inadequacy of educational systems to the requirements of the digital market, somewhat and an insufficient degree of technological sophistication in local companies. Also, the difficulties in attracting and retaining human capital with advanced digital skills directly affect the ability of these countries to produce and implement digital innovation, which perpetuates a peripheral positioning in the European technological architecture.

An intermediate category is made up of countries such as Estonia, Slovenia, Germany, France, Ireland, the Czech Republic or Croatia that record a balanced distribution between the five categories, with cyclical variations depending on the macroeconomic context or the internal policies applied during the period under analysis.

This positioning reflects the gradual transition to a mature digital economy, in which the dynamics of demand for IT specialists are strongly correlated with evolving knowledge-driven sectors. The oscillating nature of the distribution suggests that the digital transition is being strengthened and performance is not fully stabilized.

The category in question offers a fertile space for proactive public policies, which accelerate convergence with digital leaders of the continent. The analysis of the frequencies discussed above, at the country level, validates and consolidates the results of the linear discriminant analysis, indicating that the distribution of observations in the marginal categories (Very Low and Very High), is consistent with the differentiation capacity of the main discriminant function (LDA 1).

Thus, it can be concluded that these results provide the basis for a robust segmentation of European countries according to the potential for digital integration, being useful both for the analysis of economic convergence and for the formulation of strategic directions in terms of public policies. In addition, a series of analyses were generated in Figure 2 in order to broaden the spectrum of the analysis in order to cover all the analyzed variables and all the structures formed. As such, the Image in Figure 2 represents a visual synthesis of the results generated by the discriminant analysis through four two-dimensional projections, each highlighting the relationship between two discriminant functions: LD 1 vs LDA 3, LD 1 vs LD 4, LD 3 vs LD 4, LD 2 vs LD 3.

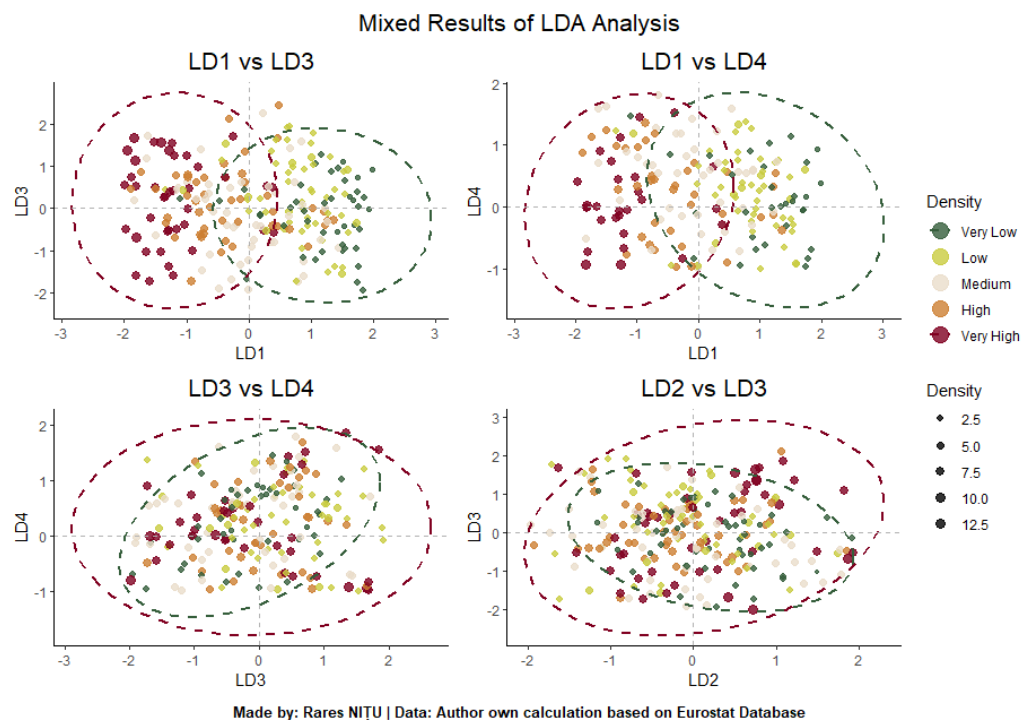
Each diagram in the collage expresses a distinct angle of the linear separation achieved between the five groups of countries classified according to the intensity of attempts to recruit IT specialists, a variable used as a reference for assessing the level of technological integration and digital sophistication. The color of the dots marks belonging to one of the cynical groups, and the size of the dots also reflects the relative insanity of the base variable. From an economic perspective, projections involving LD 1 are the most relevant, as LD 1 concentrates almost 89% of the total data variation, rethreading the strongest axis of discrimination between economies.

The separation of the dots in the four two-dimensional graphs is not only statistical, but corresponds to the economic realities in which differences in digital infrastructure, specialized human capital and innovation capacity are essential in differentiating macroeconomic performance. Projections involving discriminated LD 3 and LD 4

functions no longer show as clear separation, and significant overlaps between groups suggest that these functions capture more subtle variations, perhaps related to institutional factors, public policy cycles, or transitory characteristics of the labor market in each country.

In an economic context, this indicates that the major differences between European countries in terms of digital development are applied primarily by deep structural factors, such as the rate of integration of internal processes with digital technologies or the percentage of the workforce in technical sectors, and to a lesser extent by cyclical or microeconomic factors.

Figure 2. *Mixed Results of LDA Analysis*



Source: Authors own processing of data using RStudio (v 4.4.2).

Also, the shape and positioning of the density ellipses illustrate the degree of cohesion of each group. The complexity justifies the greater classification difficulty observed in the confusion matrix and confirms the fact that public policies aimed at these countries need to be adapted to dynamic contexts, in which differences in technological capacity are not yet well crystallized. These four representations not only provide a visual validation of the LD results, but also a coherent interpretive framework for understanding how structural differences between countries are expressed in terms of digital integration, demand for skilled labor and institutional technological maturity.

5. Conclusions

The linear discriminant analysis applied in this research allowed a structural and rigorous understanding of the model in which the indicators that have been associated with the digital transition and with regard to technological integration, lead to the differentiation of European countries according to their ability to respond to the requirements of a knowledge-based economy. The results that have been obtained have confirmed that there are some significant cleavages between the existing groups of countries, which are mainly evidenced by the first discriminant function which concentrates in its analysis close to 90% of the total variation. The LDA model was not only a reduction in dimensionlessness efficiency, but also generated a robust classification of observations, with a high accuracy in category recognition (Martindale & Lehdonvirta, 2023).

The present aspect concerns the practical usefulness of the model in the context of the comparative analysis of digital maturity, and the consistent performances obtained also through cross-validation have led to the strengthening of the generalization of the results. The errors in question, of classification, occurred especially in the area of intermediate groups that reflected difficulties in distinguishing countries in an incomplete digital transition, which suggests a high degree of institutional complexity and an unequal adaptability to modern technical standards.

Indicators such as the integration of internal processes, the share of employees in the IT sector and the gross value added generated by technology reflect structural dimensions of the digital economy. Therefore, economic policies must aim not only at increasing investment in digital infrastructure, but also at profoundly transforming private sector operating models, boosting automation, interoperability and digitalisation of value chains. Secondly, the classification of countries into five digital maturity categories revealed that uniform economic measures are ineffective. Countries in the lower categories require economic investments as a catalyst, such as subsidies for digitalisation in SMEs, tax policies to stimulate innovation or public-private partnerships in technological education (Mergel et al., 2019). At the same time, countries in the high categories, characterized by strengthened digital ecosystems, should be encouraged to adopt technological leadership policies, investments in advanced research and export of digital know-how to less developed neighboring countries. From a macroeconomic point of view, the results support the idea that specialized human capital and advanced digital integration are factors with positive effects on structural competitiveness.

Policies should, in this regard, link education, research and closure budgets with the concrete needs of the technology sector, encouraging a strategic allocation of resources in STEM areas and lifelong learning. At European level, LDA segmentation can be used as a foundation for differentiated digital convergence policies. Within the framework of the European Union's Digital Strategy or in the process of allocating the Structural Fund. Thus, a smart conditionality model can be applied, whereby states benefit from resources commensurate with commitments and results in the field of digital transformation (Mutascu, 2021).

6. Limitations and recommendations

One of the central limitations of this analysis is the use of a narrow set of indicators to characterize digitalisation and technology intensity in European economies. Although the selected variables, such as the integration of internal processes, the share of specialized employees or the contribution of the digital sector to added value, provide a good approximation of technological maturity, they do not exhaustively capture all the relevant dimensions of digital transformation, such as the quality of digital infrastructure, the intensity of investments in research and development, the level of cybersecurity or the degree of digital inclusion. In addition, the static approach by averaging the values by years reduces the ability to capture the dynamics of the digital transition and the possible external shocks that could have influenced the performance of certain states in a certain period.

To robustly improve the analysis in future research, it is recommended to expand the set of indicators with variables that more accurately capture institutional, educational and behavioral aspects relevant to the digital economy. The integration of longitudinal data and the use of panel models would allow the investigation of the causal effects and the evolution over time of the positioning of each country within the cynical categories.

Alternative classification methods, such as classification analysis or supervised machine learning models, can also be explored to compare the consistency and stability of the identified clusters. Finally, the external validation of the model, by correlating the LDA scores with the relevant macroeconomic indicators, would strengthen the explanatory value and practical applicability of the conclusions formulated.

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APPENDIX

The first table (**Table A1**) represents the statistical description of the variables before any modification or processing. The data were generated to reflect the diversity of the indicators.

Table A1. *Descriptive statistics indicators BEFORE standardized data*

	perc_ict_emp	perc_ict_gva	hrst	emp_ict	recruit_attempt	emp_tech	integration
Min.	1.230	1.990	1.200	4.00	0.5908	2.100	3.826
1st Qu.	2.469	3.660	3.400	17.70	2.9075	3.675	23.390
Median	2.955	4.307	4.950	20.45	4.2150	4.400	31.135
Mean	3.233	4.705	5.374	21.55	4.5508	4.618	31.259
3rd Qu.	3.660	5.118	7.300	25.55	5.7650	5.425	38.578
Max.	6.746	10.260	13.90	35.27	12.7000	10.200	67.260

Source: Authors own processing of data using RStudio (v 4.4.2).

Subsequently, after the standardized variables (**Table A2**) were generated, it can be observed that the mean is equal to zero for each indicator. By calculating the Z score (the method used for standardization) the indicators were modeled so that the correlations and analyses do not present any bias phenomenon, and the analyses take place without any external error.

Table A2. *Descriptive statistics indicators AFTER standardized data*

	perc_ict_emp	perc_ict_gva	hrst	emp_ict	recruit_attempt	emp_tech	integration
Min.	1.6930	1.6760	1.6350	3.1763	0.5908	-1.8345	-2.47899
1st Qu.	0.6454	0.6449	0.7732	0.6961	2.9075	0.6871	-0.71106
Median	-0.2349	-0.2456	-0.1659	-0.1993	4.2150	-0.1590	-0.01118
Mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
3rd Qu.	0.3610	0.2551	0.7547	0.7232	5.7650	0.5877	0.66136
Max.	2.9691	3.4300	3.3403	2.4827	12.7000	4.0662	3.25327

Source: Authors own processing of data using RStudio (v 4.4.2).

Table A3. *Group variable division*

	Very Low	Low	Medium	High	Very High
Austria	0	0	2	5	3
Belgium	0	1	0	3	6
Bulgari	0	5	5	0	0
Croatia	3	2	1	4	0
Cyprus	3	1	4	1	1
Czechia	0	3	2	3	2
Denmark	0	0	1	3	6
Estonia	1	2	4	2	1
Finland	0	2	1	3	4
France	1	3	2	3	1
Germany	1	0	4	1	4
Greece	5	3	0	2	0
Hungary	0	1	4	4	1
Ireland	0	4	7	9	0
Italy	6	4	0	0	0
Latvia	7	3	0	0	0
Lithuan	0	4	4	3	0
Luxembourg	0	0	0	1	9
Malta	0	0	1	1	8
Netherland	0	1	2	1	6
Poland	9	1	0	0	0
Portuga	6	2	2	0	0

	Very Low	Low	Medium	High	Very High
Romania	7	2	0	0	1
Slovakia	1	8	1	0	0
Sloveni	1	2	3	3	1
Spain	5	3	2	0	0
Sweden	0	0	3	5	2

Source: Authors own processing of data using RStudio (v 4.4.2)

RStudio Code Used for Valuation and Calculus

I. Loading the required packages

```
install.packages(c("readxl", "dplyr", "MASS", "ggplot2", "patchwork"))
```

II. Standardization of predictor variables

```
predictors <- c("integration", "perc_ict_emp", "perc_ict_gva", "hrst", "emp_ict",  
"emp_tech")
```

```
data_std <- data # copiem datele
```

```
data_std[predictors] <- scale(data_std[predictors])
```

III. Creating the grouping variable

```
quantile_breaks <- quantile(data_std$recruit_attempt, probs = seq(0, 1, length.out = 6),  
na.rm = TRUE)
```

```
data_std$group5 <- cut(data_std$recruit_attempt, breaks = quantile_breaks, include.lowest  
= TRUE, labels = c("Very Low", "Low", "Medium", "High", "Very High"))
```

```
table(data_std$group5)
```

IV. Applying linear discriminant analysis (LDA)

```
lda_model_5 <- lda(group5 ~ integration + perc_ict_emp + perc_ict_gva + hrst + emp_ict  
+ emp_tech, data = data_std)
```

```
print(lda_model_5)
```

```
preds <- predict(lda_model_5)
```

```
data_std$LD1 <- preds$x[, 1]
```

```
data_std$LD2 <- preds$x[, 2]
```

```
data_std$LD3 <- preds$x[, 3]
```

```
if(ncol(preds$x) < 4){
```

```
  data_std$LD4 <- 0
```

```
} else {data_std$LD4 <- preds$x[, 4] }
```

V. LDA model evaluation**V.I. Confusion matrix**

```
conf_matrix <- table(Actual = data_std$group5, Predicted = preds$class)
print(conf_matrix)
```

V.II.. Cross-validation (leave-one-out)

```
lda_model_5_cv <- lda(group5 ~ integration + perc_ict_emp + perc_ict_gva + hrst +
emp_ict + emp_tech, data = data_std, CV = TRUE)
confusion_cv <- table(Actual = data_std$group5, Predicted = lda_model_5_cv$class)
print(confusion_cv)
```

Digital transformation in Romania: the key factors influencing the adoption of emerging technologies

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Abstract. *Digital transformation has emerged as a pivotal driver of economic and societal change, propelled by the accelerated advancement of emerging technologies, particularly artificial intelligence (AI). In the Romanian context, this transition reveals a pronounced disparity between the country's digital potential and its structural limitations. This study critically examines the extent to which the adoption of AI and other emerging technologies can stimulate economic growth, while also emphasizing the risks associated with a digitally driven transition that lacks a coherent and inclusive reskilling strategy. By employing data from diverse sources and applying econometric modelling, the research explores the interplay between the degree of automation and digitalization in Romania and its principal determinants. The findings underscore that the effectiveness of digital transformation is fundamentally contingent upon the preparedness of the human capital to assimilate and interact with new technologies, as well as on the presence of targeted financial support mechanisms designed to facilitate such adaptation.*

Keywords: digitalization, emerging technologies, human capital, European funds, cyberattacks.

JEL Classification: C55, J24, L86, O15, O35.

Introduction

Digital transformation has become a central driver of economic and social progress, particularly in the context of the expansion of emerging technologies such as artificial intelligence (AI), the Internet of Things (IoT), cloud computing, and big data analytics (WorldBank, 2023). Romania possesses significant potential in this field - owing to its high internet speed, competitive IT sector, and youthful workforce - yet the adoption of emerging technologies remains uneven and often delayed. (Commission, 2022)

The motivation for this study lies in the pressing need to understand the key factors that either drive or hinder this adoption, particularly in a context where the digital divide may exacerbate existing economic and social inequalities. Furthermore, Romania faces structural challenges such as the low level of digital skills among the adult population, the fragmentation of reskilling initiatives, and an insufficient level of investment in emerging technologies among small and medium-sized enterprises (SMEs) (Economic, 2023).

The research question guiding this study is: "What are the key determinants of the adoption of emerging technologies within the context of Romania's digital transformation, and to what extent do these factors influence the economic performance of companies, particularly SMEs?"

Digitalization is no longer optional; it constitutes an essential condition for economic competitiveness, social inclusion, and administrative modernization, especially in the post-pandemic context and the transition toward a greener and more digital economy.

This study investigates the relationship between digitalization and economic performance (GDP, investment, unemployment), assessing the extent to which elements such as access to non-reimbursable funding, competitive pressure, global trends, and human capital influence the degree of technology adoption among economic agents.

The objectives of this paper include:

- 1) Identifying emerging technologies with strategic impact in the new economic paradigm.
- 2) Analyzing the factors influencing technology adoption in Romania.
- 3) Measuring the impact of digitalization on economic performance.
- 4) Conducting an international comparison of the degree of digitalization.
- 5) Formulating public policy recommendations to accelerate digital transformation.

Literature review

The new digital revolution requires organizations to reconceptualize their strategies, business models, and operations by adopting modern digital technologies, with the aim of generating significant added value and gaining competitive advantages. In other words, it is not merely about implementing isolated IT solutions, but about a set of profound organizational changes that enable firms to seize the opportunities created by emerging technologies. (Verhoef, 2021). The specialized literature highlights the complex and interdisciplinary nature of digital transformation, involving technological dimensions as

well as change management processes, organizational culture, and the adaptation of human capital to new realities (Nadkarni&Prügl, 2021)

Within this framework, Romania faces a digital paradox: on one hand, it holds significant structural advantages - among the fastest internet speeds globally, a high-performing IT sector, and young people with outstanding technical achievements. On the other hand, Romania consistently ranks among the lowest in European digitalization indexes (DESI), revealing major deficiencies in digital education, e-governance, SME digitalization, and institutional infrastructure. For example, a significant share of the adult population lacks basic digital skills, and participation in lifelong learning is among the lowest in the EU (Commission, 2022).

Unlike simple digitization processes, limited to data conversion and workflow automation, digital transformation requires a fundamental reorientation of organizations, involving internal structural changes, cultural adjustments, and skills development so that technology becomes central to value creation. The historical evolution of the concept is closely tied to technological progress. Early waves of digitalization appeared in the second half of the 20th century (with the introduction of computers, the Internet, and mobile telecommunications), laying the foundation for the modern digital economy. A turning point was the launch of the Industry 4.0 initiative in 2011, highlighting the potential of widespread integration of technologies like the Internet of Things (IoT), intelligent robots, and big data analytics into industrial production processes. The Industry 4.0 concept - often referred to as the fourth industrial revolution - emphasized the vision of smart factories where physical and digital systems work closely together to increase efficiency and enhance production customization (Schwab, 2016)

Subsequently, rapid advancements in fields such as artificial intelligence (AI), cloud computing, and blockchain (post-2010) expanded digital transformation beyond manufacturing, enabling the emergence of innovative digital business models in financial services, healthcare, education, and public administration (OECD, 2020). Thus, digital transformation has evolved into a continuous and ubiquitous process, becoming a key driver of economic modernization and competitiveness across all sectors. Contemporary definitions emphasize this dynamic: for instance, Vial (2019) describes it as "a process aimed at improving an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies." Essentially, the concept involves the strategic use of technology to achieve innovation in products and services, greater operational efficiency, and flexibility in response to market changes, all defining characteristics of the contemporary digital economy (Vial, 2019).

Table 1. *Trigger Factors of Digital Transformation*
(Industry 4.0 vs Industry 5.0)

Category	Industry 4.0	Industry 5.0
Trigger factor T	Technological revolution: automation, digitalization, connectivity	The need for a human-centered, sustainable, and resilient economy
Focus	Efficiency, speed, productivity	Human-centered, sustainability, well-being
Motivation	Economic growth through technology	Using technology for sustainable and inclusive development
Key technologies	IoT, big data, cloud, robotics, cyber-physical systems	Collaborative AI, green technologies, digital ethics, advanced personalization

Category	Industry 4.0	Industry 5.0
Human-technology relations	Automation replaces human labor in repetitive processes	Human-machine cooperation, focused on human skills and creativity
Specific skills	Technical (programming, operating automated systems)	Digital + socio-emotional (creativity, ethics, critical thinking)
Sustainability	Marginal (energy efficiency as an indirect result)	Central (sustainability becomes a strategic goal)
Challenges	Complexity of industrial processes, demand for personalization	Global crises, climate change, social inclusion, economic resilience

Source: Author's own processing

Digital transformation, driven by emerging technologies, is today recognized as a major catalyst of global economic growth. The introduction of innovations such as artificial intelligence, robotic automation, blockchain, virtual/augmented reality, 3D printing, and others has significantly enhanced productivity across nearly all industries, generating added value. Studies highlight that digital technologies stimulate innovation and efficiency, thereby contributing to GDP growth and the creation of highly skilled jobs (Kaggwa, 2023).

A key dimension of the impact of these technologies is the creation of new markets and business models. Digital innovations have given rise to entirely new industries - from the mobile application economy and digital platforms (Uber, Airbnb, sharing economies) to the data storage and artificial intelligence sectors - which have opened up unprecedented growth opportunities (McAfee, 2017). Companies that have embraced digital transformation have succeeded in expanding their global reach and achieving rapid scalability (for instance, SaaS, PaaS, and IaaS platforms allow firms to reduce licensing or server costs, provide remote data accessibility, and enhance scalability). Simultaneously, the use of advanced data analytics techniques and machine learning algorithms enables firms to innovate more quickly, anticipate market trends, and improve decision-making processes - all translating into higher aggregate economic growth (Agrawal, 2022).

Emerging technologies also contribute to improving the quality and diversity of production, thereby stimulating demand. For example, in the healthcare sector, 3D printing enables the production of personalized medical devices, while AI significantly enhances diagnostic accuracy (by comparing results with millions of patient patterns), increasing treatment efficacy and, indirectly, labor productivity (OECD, 2024). In agriculture, IoT sensors and smart drones optimize crop yields (precision agriculture), with the potential to increase rural incomes and contribute to food security. These examples illustrate how the adoption of cutting-edge technologies can boost growth not only through increased volumes but also through the superior quality of goods and services offered on the market.

However, it must be emphasized that the positive impact of digital transformation on economic growth is not automatically guaranteed for all stakeholders. Significant disparities exist between countries and sectors in terms of digitalization levels. The digital divide remains a pressing challenge: for example, advanced economies currently reap the largest share of the economic benefits from new technologies, while emerging economies risk falling behind if they fail to sufficiently invest in digital infrastructure and skills. Moreover, emerging technologies may also have disruptive effects - some jobs become redundant, and traditional firms may be overtaken by more digitalized competitors -

meaning that digitalization-driven growth is accompanied by the need for adaptation. Nevertheless, the overall consensus in the specialized literature is that the net effect of digital transformation on the economy is positive: the widespread adoption of new technologies tends to lead to faster economic growth, higher macroeconomic productivity, and greater innovation, provided that society invests in mitigating risks and preparing for the transition. Furthermore, technologies such as artificial intelligence are regarded as "game-changers" - they could significantly push forward the frontiers of efficiency and scientific progress, adding notable percentages to medium-term economic growth rates. Provided that appropriate policies are implemented (in areas such as education, competition, and data security), the role of emerging technologies will remain central in fostering sustainable economic growth, while also facilitating development objectives such as environmental sustainability (through green technologies and resource optimization) and social inclusion (through expanded access to digital services).

Cyberattacks and Digital Security

The rapid digitalization of economies and societies yields numerous benefits, but it also introduces significant challenges, most notably in the realm of cybersecurity. As an increasing number of activities transition to the digital sphere, the vulnerability to cyberattacks experiences a corresponding surge.

These attacks can manifest in a variety of forms, encompassing data breaches, ransomware incidents, denial-of-service attacks, and phishing schemes, with both public and private entities as potential targets. The ramifications of cyberattacks can be severe, leading to financial losses, damage to reputation, disruptions in essential services, and even posing threats to national security. In Romania, for example, the growing prevalence of cloud computing and the proliferation of IoT devices within sectors like energy and healthcare elevate the susceptibility of these critical industries to cyberattacks. To mitigate these risks, it is imperative that organizations and governmental authorities prioritize the implementation of robust cybersecurity measures. These measures should include the deployment of advanced threat detection systems, data encryption techniques, the execution of regular security audits, and the provision of comprehensive employee training on cybersecurity best practices. Furthermore, given the transnational nature of cyber threats, international cooperation and the development of shared cybersecurity standards are of paramount importance in effectively addressing these challenges. Ultimately, investing in cybersecurity should be viewed not merely as an expenditure but as a fundamental necessity. It is essential to safeguard the advantages of digitalization and to foster trust and security within digital environments.

Human capital and the challenges of *reskilling* in a digital economy

In a digital economy, human capital is just as important as technological investments. Employees' skills, knowledge, and abilities determine how quickly and effectively a

technology can be adopted. (OECD, 2021) Artificial intelligence (AI) in particular requires a workforce capable of understanding, implementing, and using these intelligent solutions. The digital transformation is accelerating the demand for new skills: data analysis, software development, the use of AI algorithms and cybersecurity. Employees must be prepared to continuously learn, or even retrain to remain relevant in the labor market. World Economic Forum 2025 (WEF, 2025) estimates that by 2030, more than one billion people will need at least one retraining due to the emergence of new technologies. Today, the digital skills gap is visible. At the level of the European Union, only 54% of adults have basic digital skills in 2021, well below the target of 80% of the share set for 2030 according to Eurostat 2023. (Comission, 2023) The lack of AI specialists and related fields is becoming a major barrier to the adoption of new technologies. (OECD, 2023) For example, between 2019 and 2020, job ads asking for AI skills increased by 33% (OECD, 2023).

Companies, especially SMEs, need to implement internal training programs and collaborate with training centres to lead to solving these gaps. Not only IT specialists are targeted, but also organizational leaders need to understand the impact of technology on business models. In this context, reskilling and digitalization programs become essential tools. Initiatives such as the European Skills Agenda and the European Digital Programme, (Comission, 2023) supports the development of advanced digital skills. Governments are also called upon to invest in expanding access to fast internet and to stimulate training in emerging technologies, especially in rural or disadvantaged areas.

The adoption of AI and digitalization does not mean a technological change, but also a human transition. Employees need to be supported, continuous learning methods are being developed, and organizations need to integrate digital training into their development strategies. In the end, the success of digitalization depends not only on technology, but especially on people.

Vocational education and training are essential for preparing human capital in a digital economy. The benefits of digitization on economic growth depend on the level of digital skills in society, which requires the reform of the education system. Disciplines in schools and universities need to be updated to include skills such as the use of digital tools, programming, artificial intelligence and critical thinking. Universities should also work closely with industries to develop relevant practical programs and internships. (Comission, 2023)

Methodology

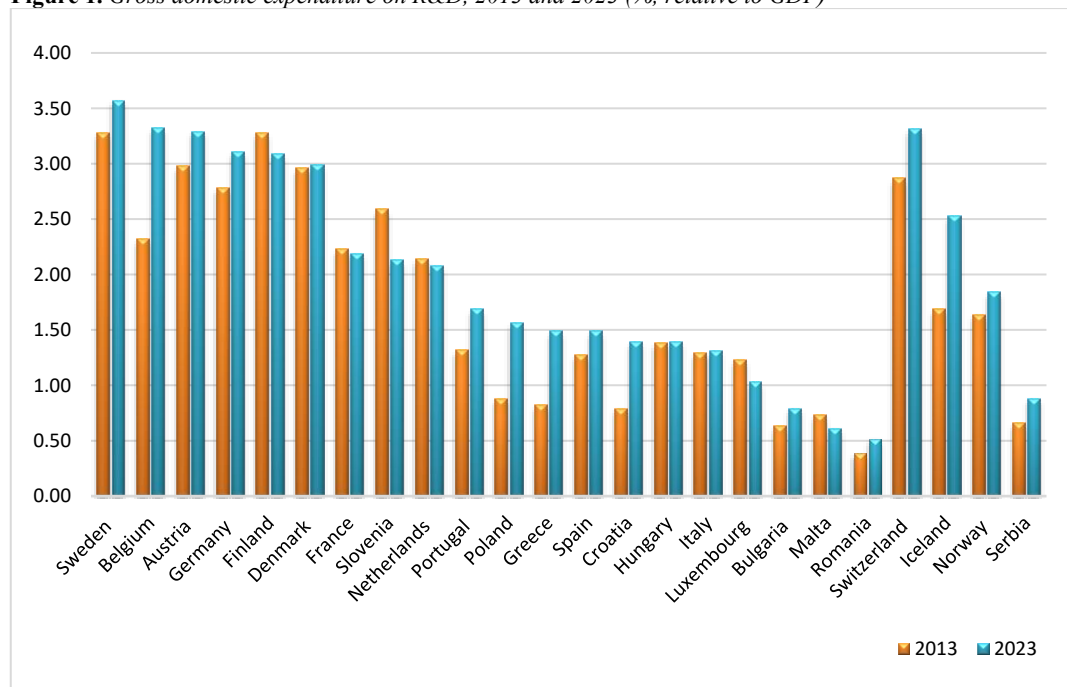
The study uses a quantitative methodology, based on the construction of a *panel econometric model*, applied to a sample of 10 countries with a *high level of adoption of AI and emerging technologies*, for the period 2014–2024. The methodological structure includes *the collection of data* from official sources (Eurostat, OECD, World Bank, AI Index) for indicators such as: GDP per capita, unemployment rate, output per hour worked and foreign direct investments. We will analyse the impact of these technologies on

economic growth, GDP, unemployment and investment in technology with the help of a representative econometric panel. We will draw attention to the systemic challenges that affect the success of the digital transformation – in particular the lack of digital skills and coherent reskilling strategies, and then formulate public policy recommendations and strategic interventions that accelerate the digitization process in a sustainable and equitable way.

The data panel analysis was used to identify the impact of digitalization on key economic variables: economic growth, tech investment, GDP/capita and unemployment. Hypothesis testing (which) was performed by fixed-effect regressions, using robust standard errors to control for econometric problems (autocorrelation, heteroscedasticity). This approach allows the impact of digitalization to be isolated from other structural factors and provides a solid empirical basis for policy-making.

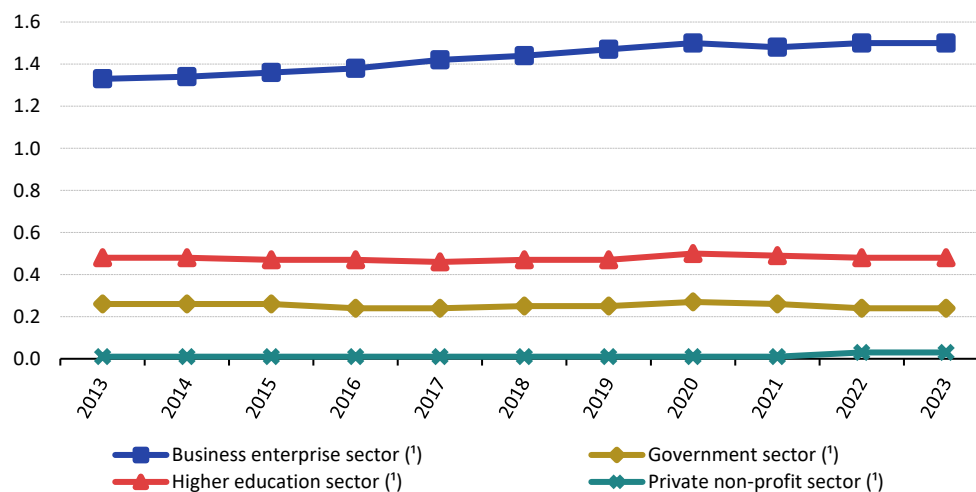
Results and discussions

Figure 1. Gross domestic expenditure on R&D, 2013 and 2023 (% relative to GDP)



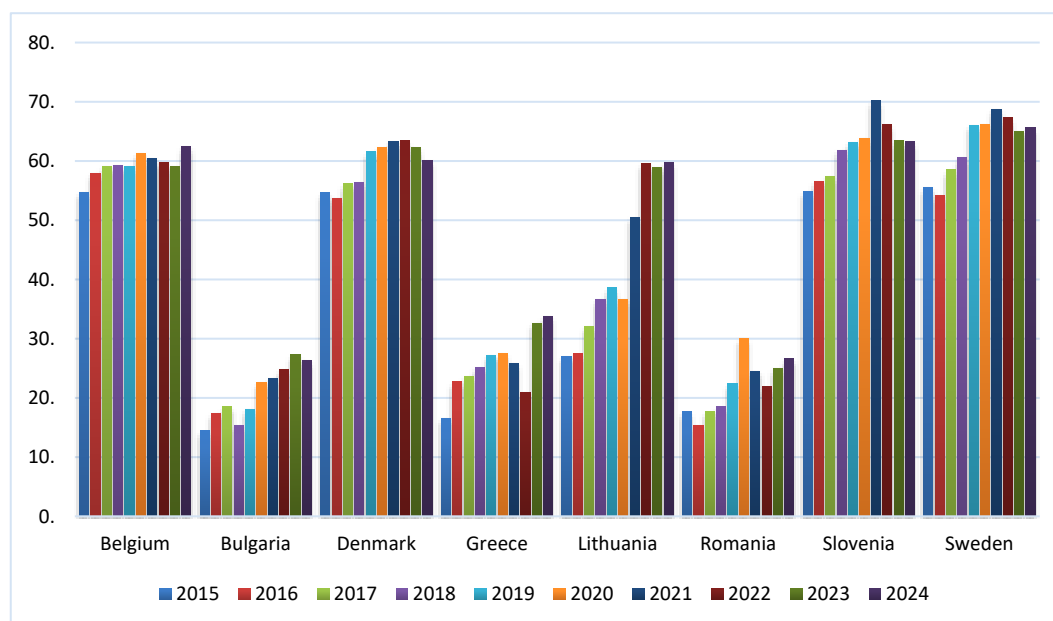
Source: Authors' own computation from Eurostat database.

Figure 1. shows significant disparities in R&D spending across European countries. Sweden, Belgium and Germany lead with over 3% of GDP allocated to R&D in 2023, while countries like Romania and Serbia, though starting from low levels, show notable growth. Others, such as Ireland and Norway, exhibit stagnation or slight declines. Overall, the data reflects uneven progress toward strengthening national innovation systems.

Figure 2. Gross domestic expenditure on R&D by sector, EU, 2013-2023 (% relative to GDP)

Source: Authors' own computation from Eurostat database.

This figure reveals that the business enterprise sector dominates R&D expenditure in the EU, with a steady increase over the decade. The higher education and government sectors remain stable, while the private non-profit sector contributes minimally. The overall structure of R&D investment remains relatively unchanged, emphasizing the key role of private industry in driving EU innovation.

Figure 3. E-commerce sales of enterprises by size class of enterprise

Source: Authors' own computation from Eurostat database.

This figure illustrates a general increase in e-commerce adoption among enterprises across all observed countries from 2015 to 2024. Northern and Western European countries (for example Sweden, Denmark, Belgium) show consistently high levels, while Eastern European countries (like Bulgaria, Romania, Greece) demonstrate strong growth in recent years, likely accelerated by digital transformation trends post-2020.

Table 2. *Main Coefficients*

Variable	Coefficient	p-value	Economic Interpretation
Output per hour worked	+1 785	0.019	A 1 USD (PPP 2021) increase in hourly productivity raises GDP per capita by approximately 1,800 USD. Labor productivity is by far the dominant driver of living standards.
FDI (% din PIB)	+ 841	0.049	A one-percentage-point increase in foreign direct investment (relative to GDP) adds, on average, around 840 USD to GDP per capita. FDI brings capital, know-how, and access to markets
Unemployment rate	-1 458	0.067	A one-percentage-point increase in unemployment reduces GDP per capita by approximately 1,460 USD. The economic cost of unemployment is substantial, even though the coefficient is at the threshold of statistical significance.

Source: OECD, WORLD BANK, LABOUR DATA

Overall model statistic: $R^2 = 0.982$ - the model explains over 98% of the variation in GDP per capita when controlling for permanent country differences and common yearly shocks.

Economic Lessons:

- 1) Labor productivity is the key to prosperity: Investments in technology, digitalization, and advanced skills have a direct and substantial effect on living standards.
- 2) Foreign direct investment truly matters: FDI amplifies available capital, but the impact remains positive only if projects have high added value and strong local linkages.
- 3) Unemployment remains a significant burden: Idle labor resources lower national income; active labor market policies can generate quick economic gains.

Table 3. *Policy Recommendations*

Objective	Priority Measures	Anticipated Impact
Boosting productivity	- Tax incentives for automation and R&D - Rapid upskilling/reskilling programs in digital fields - Digital infrastructure for SMEs	+1,800 USD per 1 USD increase in output per hour
Attracting quality FDI	High-tech "plug-and-play" industrial parks After-care services for profit reinvestment	+840 USD per +1 pp increase in FDI/GDP
Reducing unemployment	• Temporary subsidies for hiring vulnerable groups • Digital job-matching platforms • Dual education and rapid retraining programs	Avoids ~1,460 USD loss per +1 pp increase in unemployment

Source: Author's own processing.

Limitations

Possible moderate collinearity effects (condition number $\approx 4,000$) which could dilute the significance of the unemployment coefficient. The model captures the average effect; impacts may vary across countries depending on economic structure. Results are based on aggregate data; sectoral analyses could provide additional insights.

Conclusion

Raising labor productivity and attracting high value-added foreign investments are the most reliable ways to rapidly increase GDP per capita, while active labor market policies complement these efforts by mitigating the economic losses generated by unemployment.

Digital transformation represents a fundamental condition for economic competitiveness, and its successful implementation directly depends on the ability of organizations to integrate emerging technologies within a coherent strategic framework that encompasses both technological infrastructure and human capital development. The adoption of digital technologies by SMEs has a significant impact on operational efficiency and the expansion of market access; however, the real benefits are conditional upon active leadership involvement and employees' willingness to adapt through upskilling and reskilling processes.

The accelerated digitalization of economies and societies brings numerous benefits but also generates significant challenges, particularly in the area of cybersecurity. As more activities migrate to the digital space, vulnerability to cyberattacks increases proportionally. The development of digital competencies has become a cross-sectoral priority in both education and the economy, as the shortage of technological skills severely limits society's ability to fully harness the potential of new technologies. Partnerships between educational institutions, industry, and the public sector are essential for creating a training ecosystem aligned with the needs of the digital labor market, thus ensuring a strong correlation between educational offerings and the demand for emerging skills.

Public policies supporting digitalization must be complemented by active measures for digital inclusion in order to avoid deepening social and economic disparities and to ensure a fair and sustainable digital transition at the national level. Further research could explore the specific impact of digital transformation on different sectors of the Romanian economy, such as agriculture, manufacturing, and services. Comparative analyses with other countries in the region could identify best practices and policy recommendations tailored to the Romanian context.

Additionally, research on the ethical implications of AI and the governance of digital technologies is needed to ensure responsible and sustainable digital transformation.

The analysis of digital transformation emphasizes the need for proactive intervention by governments and European institutions. The econometric results (2019–2024) confirm that the adoption of digital technologies positively stimulates GDP growth and long-term productivity. However, several limitations should be acknowledged.

First, the availability and completeness of data vary significantly across countries, which may affect the comparability of results. Second, the chosen time frame (2019–2024) coincides with the COVID-19 pandemic, a period marked by extraordinary disruptions in industries and labor markets. Consequently, the observed effects may partially reflect pandemic-induced shocks rather than the pure impact of digital transformation.

Furthermore, structural differences between sectors and the uneven pace of technology adoption across regions could introduce additional biases. Lastly, the analysis relies heavily

on macroeconomic indicators, which may not fully capture micro-level dynamics, such as firm-specific adoption strategies or individual skill gaps.

Despite these limitations, the study offers valuable insights into the key factors influencing the adoption of emerging technologies in Romania and outlines essential policy priorities for a sustainable digital transition.

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Methods for conducting risk analysis in external public audit of public procurement using AI-based algorithms

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Abstract. *Artificial intelligence, one of the most widely used concepts today, has demonstrated its efficiency in various fields of activity. The benefits of AI-based tools have also been observed in the field of external public audit, particularly because auditors often need to analyze large databases within a relatively short time to identify potential irregularities.*

This article aims to present AI-based tools that can be used for risk analysis in public procurement during external public audit missions conducted by the Romanian Court of Accounts.

Keywords: external public audit, Romanian Court of Accounts, risk analysis, public procurement, artificial intelligence.

JEL Classification: H570, H75, H76.

Introduction

According to data from the European Commission (The 2025 Annual Single Market and Competitiveness Report), over 250,000 public authorities within the European Union spend approximately 14% of GDP on the procurement of goods, services, and works. This significant share of public funds allocated to public procurement naturally exposes the sector to risks of fraud and corruption, necessitating increased attention to this area.

Public procurement systems in EU member states are required to ensure transparency in procurement processes by collecting all relevant information on awarding procedures within databases accessible to the general public. In conducting audit missions for public sector entities, the Court of Accounts can perform risk analysis regarding the public procurement carried out by these entities. The methods used for this risk analysis may include AI-based tools, which can bring significant advantages to audit missions.

1. AI-Based Risk Analysis Tools Used in Audit

The use of AI-based tools has become a common practice in major auditing corporations, particularly within the Big Four.

KPMG employs a variety of tools and methods for risk analysis in its audit engagements. One of these tools is **Clara** (<https://kpmg.com/xx/en/what-we-do/services/audit/kpmg-clara.html>), a cloud-based digital platform that supports audit teams throughout the audit process. This platform utilizes artificial intelligence to analyze data, identify risks, and assess the internal control system of the audited entity. However, Clara is not the only tool of this kind. KPMG also employs several other AI-based tools, including **data analytics tools, risk-based audit approaches, internal control frameworks, scoring and risk models**, as well as **process automation** tools.

Regarding risk analysis, one of KPMG's most significant AI-based tools is **Alteryx** (<https://www.alteryx.com/>), a platform that integrates AI-driven risk analysis. It uses automation tools to collect, move, and transform data. Additionally, KPMG leverages **data automation tools** that allow auditors to process large volumes of transactions and data to identify potential risks efficiently.

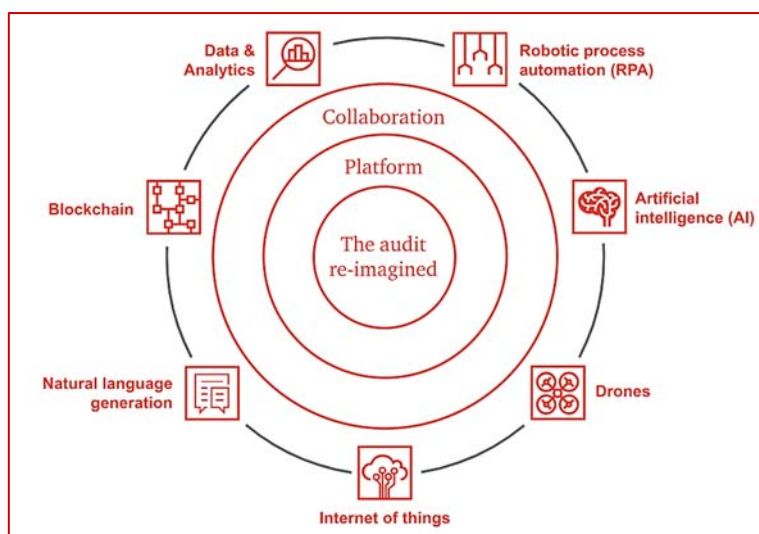
Deloitte also incorporates AI-powered tools into its audits, such as **DataDoc** (<https://www.deloitte.com/de/de/products/aistudio/anomaly-detector-consistency.html>). This tool can detect various potential irregularities by generating a preliminary shortlist that serves as the foundation for detailed audit testing. DataDoc creates this shortlist based solely on statistical approaches, without prior knowledge of the content of the analyzed data. It employs sophisticated methods such as **automatic encoding and principal component analysis** to pinpoint the most relevant characteristics where anomalies occur. The results are displayed in a **visual and interactive format**, enabling auditors to analyze aggregated and individual data intuitively and select samples for audit procedures based on their professional judgment.

Additionally, **Deloitte Omnia AI** (<https://www2.deloitte.com/ca/en/pages/deloitte-analytics/articles/omnia-ai-capabilities-services.html?icid=omnia-ai-capabilities-services>) is an AI-driven audit platform that helps audit teams automate the process of data collection and analysis. This platform integrates **machine learning and natural language processing (NLP)** technologies to analyze and assess clients' financial data. It enhances audit efficiency and accuracy, allowing auditors to focus more on high-risk areas.

Another AI-based tool used by Deloitte is **Cortex** (<https://www2.deloitte.com/ca/en/pages/deloitte-analytics/articles/cortex-ai.html>), which automates document and financial data analysis. It leverages **advanced NLP and machine learning techniques** to extract valuable information from unstructured documents such as contracts, invoices, and financial reports. By automating many routine audit tasks, Cortex significantly accelerates the audit process and enhances overall efficiency.

Like the other major audit firms in the Big Four group, **PwC** employs numerous AI-based tools in its audit activities. The main AI-driven tools and techniques used by PwC are presented in **Figure 1** below:

Figure 1. Key AI-Based Techniques, Tools, and Processes Used by PwC in Audit Activities



Source: <https://www.pwc.ro/ro/servicii/servicii-audit-financiar-servicii-non-audit.html>

Aura is PwC's audit platform, integrating advanced AI and machine learning technologies to automate multiple audit processes. Aura supports auditors in quickly accessing financial data and detecting risks and anomalies during financial audit engagements. Additionally, Aura helps identify and manage risks by analyzing financial data in real-time. Its AI algorithms can detect patterns and anomalies that may indicate fraud risks, accounting errors, or compliance issues. (<https://www.pwc.com/us/en/services/audit-assurance/financial-statement-audit/aura-audit-technology.html>)

PwC's GL.ai is another AI-powered tool used in auditing, which not only enables rapid identification of errors, fraud, and non-compliance but also provides real-time access to

clients' financial data. This allows for real-time analysis of transactions performed by clients. The platform is designed for dual usage—both by audit teams and the audited company—ensuring that both parties have access to the same type of data. This feature significantly enhances communication between audit teams and clients. (<https://iaf-febui.com/unveiling-the-power-of-gl-ai-transforming-financial-statement-for-business-to-be-better/>)

Similar to other major audit firms, **Ernst & Young (EY)** utilizes AI-driven audit tools to support its audit teams. One of these tools is **EY Helix**, a suite of AI-based data analytics tools that allows audit teams to perform detailed financial data analyses, identify risks, and enhance the audit process through automation and accelerated data collection and evaluation. (https://www.ey.com/en_gl/services/audit/technology/helix)

EY Canvas is Ernst & Young's global audit platform that integrates AI-powered tools to help audit teams collaborate more effectively and collect and analyze financial data in real time. Canvas also leverages AI to support risk identification and automate various aspects of the audit process, such as transaction reconciliation and verification (https://www.ey.com/en_gl/services/audit/technology/canvas).

As seen from the discussion above, AI-based tools used in the private sector by **Big Four** firms in audit activities effectively contribute to reducing the time required for repetitive tasks. This enhances the efficiency of audit teams, allowing them to focus on high-risk areas during audit engagements.

Furthermore, there is a direct correlation between the extent of AI tool utilization in audit firms and their performance. The use of these tools leads to shorter audit engagements, higher-quality audit reports, and an increased number of assignments, which can, in turn, contribute to business growth and a larger client base.

2. Artificial Intelligence-based Tools Used in External Public Audit

Regarding the public sector, things are somewhat different. The implementation of artificial intelligence-based tools has been somewhat delayed compared to the private sector, due to various reasons, one of which is related to data security and the public authorities' mistrust in the ability of these tools to ensure the confidentiality of the data used, especially that of a control nature.

Within supreme audit institutions, there is a growing concern about using artificial intelligence-based audit tools, as they could significantly reduce the time allocated by audit teams for routine tasks. They can also contribute to risk analysis by analyzing large databases and selecting elements that show anomalies.

In November 2024, INTOSAI (International Organization of Supreme Audit Institutions) organized the "Global Summit on Audits by Supreme Audit Institutions Contributing to Digitalization and Sustainability" in Georgia (<https://www.idi.no/news/idi-news/global-summit-2024-supreme-audit-institutions-contribution-to-sustainability-and-digitalisation>), with support from the Supreme Audit Institution of Georgia. This summit was an

opportunity for the collective efforts of supreme audit institutions to discuss current trends regarding digitalization and sustainability in the public sector. The summit was attended by heads of supreme audit institutions, international organizations, academic representatives, and stakeholders from nearly 30 countries. The summit highlighted the transformative impact of digitalization on supreme audit institutions, focusing on both the opportunities and challenges this phenomenon presents. It also presented information on leveraging advanced technologies such as artificial intelligence and blockchain to streamline audit missions, improve data analysis, and accuracy, concluding that this rapid change still requires ongoing development of auditor competencies in the public sector and significant investment in resources, especially for smaller supreme audit institutions.

At the EUROSAI (European Organization of Supreme Audit Institutions) level, there is also considerable concern regarding the use of artificial intelligence. For example, since 2021, EUROSAI's IT Working Group has organized a seminar titled "From Code to Action: Supreme Audit Institutions in the World of Artificial Intelligence," which was attended by representatives from 50 supreme audit institutions worldwide. One of the discussion topics was identifying the possibilities of using artificial intelligence in external public sector auditing and the auditing of algorithms based on artificial intelligence used by entities in the public sector (<https://intosaijournal.org/journal-entry/eurosai-it-working-group-ai/>). Also, during the 12th EUROSAI Congress in June 2024, the future of auditing and public sector auditors was discussed, considering the rapid development of artificial intelligence tools (<https://lrvk.gov.lv/en/news/at-the-xii-eurosai-congress-the-role-of-artificial-intelligence-in-public-sector-auditing-is-outlined>).

Regarding public procurement, the use of artificial intelligence-based tools in risk analysis by supreme audit institutions can be beneficial for identifying and managing risks related to transparency, fraud, and payments made for non-delivered goods, services, and works.

A concrete example of the use of artificial intelligence in external public sector auditing is the development of four applications by **Brazil's supreme audit institution**, which are capable of identifying fraud and corruption situations, particularly in the area of public procurement (Odilla F., 2023).

ALICE, one of the tools used by external public auditors in Brazil's supreme audit institution, is based on artificial intelligence and involves number and text analysis, being capable of learning from information provided by users. This application is interconnected with Brazil's public procurement system, Compasnet, where all procurement procedures conducted by Brazilian public entities are uploaded daily. After collecting the necessary information, ALICE tests the identified typologies (possible irregularities) (Neves F.R., da Silva P.B., de Carvalho H.L.M., 2019).

ADELE, another tool used by Brazil's supreme audit institution based on artificial intelligence, can display data entered by public authorities in Brazil's procurement system in graphical images, making it possible to obtain information about the competition between economic operators participating in award procedures (Neves F.R., da Silva P.B., de Carvalho H.L.M., 2019).

MONICA is another tool used by Brazil's external public auditors, based on artificial intelligence, which identifies all public procurement procedures, including those that ALICE may overlook, such as direct procurements (Neves F.R., da Silva P.B., de Carvalho H.L.M., 2019).

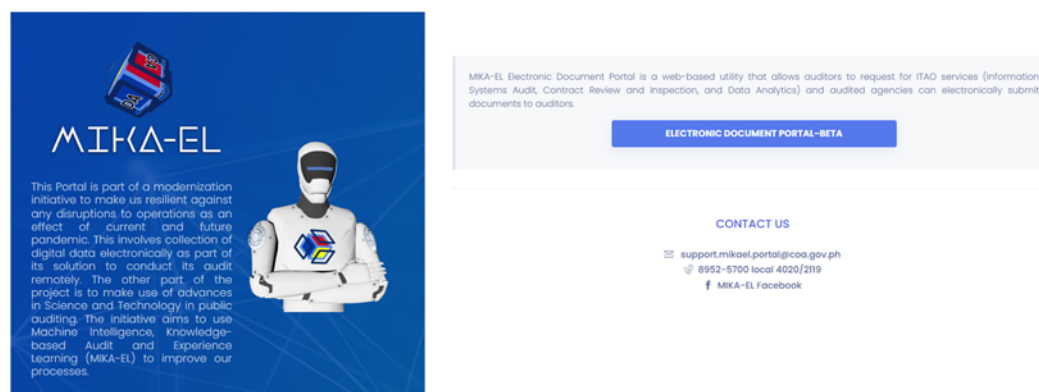
SOFIA is perhaps the most comprehensive tool used by Brazil's supreme audit institution, which acts as an automated assistant for external public auditors based on existing elements in the institution's database, namely the Brazilian Federal Court of Audit (Neves F.R., da Silva P.B., de Carvalho H.L.M., 2019).

India's Supreme Audit Institution (SAI India) also uses artificial intelligence-based tools, developing a protocol designed to streamline and accelerate audit report writing. The new artificial intelligence-based protocol will optimize data collection during audit missions, data cleaning, classification, and analysis processes, leading to substantial improvements in audit reports (https://ai.icaai.org/articles_details.php?id=113).

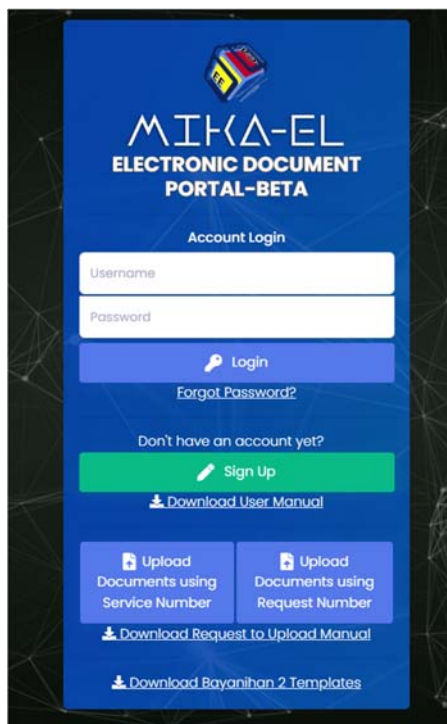
SAI Costa Rica has been using artificial intelligence in its public procurement audits since 2020, implementing a predictive model based on the "modeling-learning-implementation" technique. By adding new information about already analyzed contracts, SAI Costa Rica has generated large amounts of data that have helped develop a machine learning system. This system can automatically analyze certain contracts and alert the supreme audit institution to contracts that present a high risk (INTOSAI Journal of Government Auditing, 2021).

The MIKA-EL (Machine Intelligence, Knowledge-based Audit, and Experience Learning) project is an artificial intelligence-based tool used by SAI Philippines, functioning as an audit assistant, processing large volumes of data, and helping auditors sort and process data quickly and efficiently. This system allows the analysis of information transmitted by entities in the Philippine public sector to the external public auditors of SAI Philippines, which is analyzed during audit missions (<https://mika-el.coa.gov.ph/Login>). The interface allows each user to log in with a user ID and password, as shown in Figures 2 and 3 below:

Figure 2. *The MIKA-EL system interface*



Source: <https://mika-el.coa.gov.ph/>

Figure 3. Access method to the MIKA-EL system

Source: <https://mika-el.coa.gov.ph/Login>

The analysis of the information presented within the MIKA-EL data analysis platform is carried out through Excel files, which contain templates with data that need to be completed by the audited entities. These files are then imported into the MIKA-EL platform by the audited entities and analyzed by the external public auditors of the Philippine SAI within the section specifically allocated for data analysis related to their audit missions.

These are just a few examples of artificial intelligence-based tools currently used by a number of supreme audit institutions in their specific external public audit activities, with the benefits of using them being reflected in their audit reports, which are based on in-depth analysis, including the identification of risk areas in various fields. In fact, there is a belief among some authors that supreme audit institutions must align with the practices used in audits, including those in the private audit sector, where these techniques have been intensively used by auditors for several years (Otia, J. E., Bracci, E., 2022).

3. Analysis of an Excel Database Extracted from SEAP with Award Notices for Public Procurement Contracts Concluded in the Pandemic Year 2020 Using Two Artificial Intelligence-Based Algorithms

In order to perform a risk analysis in the field of public procurement, I extracted a database from SEAP containing all public procurement procedures from the pandemic year 2020, conducted by public entities in Romania, with the object of purchasing medical equipment, sanitary materials for the prevention and combating of the spread of the SarsCov2 virus, as well as medicines. The database was exported into an Excel file and contains 10,894 award notices for public procurement contracts published by public authorities in Romania, primarily healthcare units.

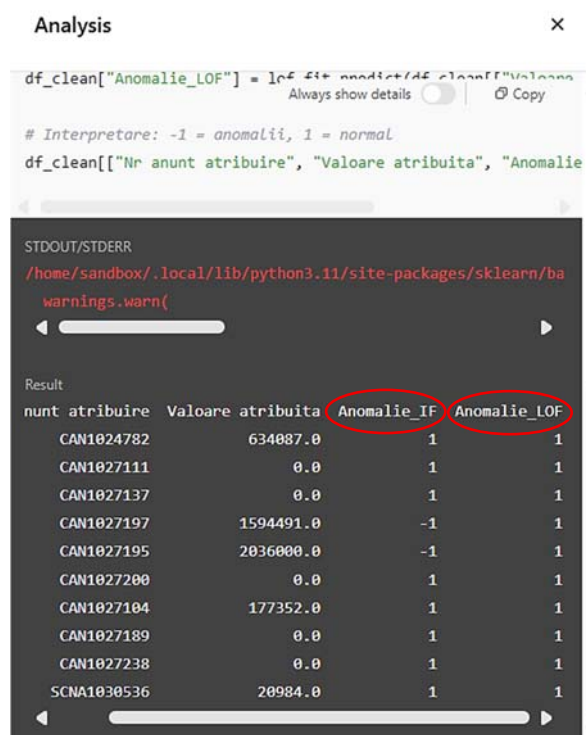
The imported database was "cleaned" as in some cases the contract values were expressed differently and had to be converted into a numeric format. Additionally, there were text fields that needed to be cleaned. After preparing the database, it generated a total of 9,650 award notices regarding contracts concluded by public entities in Romania. Of these, 7,073 contracts had valid assigned values. These 7,073 entries in the database were analyzed using machine learning and artificial intelligence methods, specifically with the use of two algorithms: Isolation Forest and Local Outlier Factor. The request to perform these analyses was made with the help of ChatGPT, in order to identify suspicious contracts from the

database, which could then be analyzed individually based on the auditor's professional judgment.

The Isolation Forest and Local Outlier Factor algorithms identified suspicious contracts, generating anomalies. Contracts with large values (over 1.5 million RON) were flagged as anomalies by Isolation Forest, but not by the other algorithm, Local Outlier Factor.

Subsequently, the two analyses generated by the two algorithms were compared by ChatGPT to highlight the most suspicious award notices for the corresponding contracts, generating a combined analysis, the results of which are presented in Figure 4 below:

Figure 4. Results of the analysis using the Isolation Forest (IF) and Local Outlier Factor (LOF) algorithms regarding the most suspicious public procurement procedures.



Source: generated by authors.

As shown in Figure 4 above, the analysis identified a number of award notices corresponding to the most suspicious public procurement procedures conducted by entities in the public sector, which can be individually analyzed by external public auditors by accessing SEAP and requesting additional information from the relevant entities. Additionally, it can be observed that contracts with a zero value were identified, as well as high-value contracts detected as anomalies by both algorithms. Most of these contracts were concluded through negotiation without prior publication of a participation notice, one of the most non-transparent procurement procedures regulated by European legislation and implemented at the national level in Romania.

After this analysis, a final report regarding the suspicious contracts was requested, and these are presented in Figure 5 below:

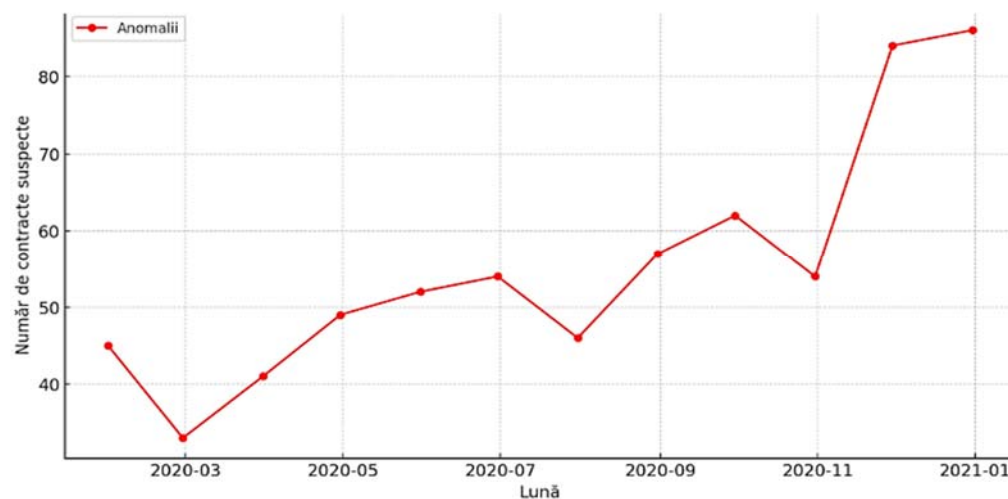
Figure 5. Final report on suspicious contracts

Analysis			×
Nr anunt atribuire	Den		
2958	CAN1032486	Achiziție de echipamente de protecț	
9254	CAN1047208	Acord-Cadru ce are ca obiect achizi	
8733	CAN1046370	Acord-Cadru ce are ca obiect achizi	
9251	CAN1047204	Acord-Cadru ce are ca obiect achizi	
2300	CAN1033297	Acord-cadru pentru furnizarea d	
7001	CAN1043274	Solutii tehnice pentru dotare Sali	
9253	CAN1047206	Acord-Cadru ce are ca obiect achizi	
2916	CAN1033813	Extindere sistem integrat telemedic	
2016	CAN1032817	Achiziție Echipamente de protecție	
6699	CAN1028656	Furnizare, instalare si amenajare s	
Tip procedura			Valoare atribuita
2958	Negociere fara publicare prealabila		301620150.0
9254	Negociere fara publicare prealabila		107310000.0
8733	Negociere fara publicare prealabila		91500000.0
9251	Negociere fara publicare prealabila		82500000.0
2300	Negociere fara publicare prealabila		72083910.0
7001	Licitatie deschisa		66505680.0
9253	Negociere fara publicare prealabila		57900000.0
2916	Negociere fara publicare prealabila		54000000.0
2016	Negociere fara publicare prealabila		45000000.0
6699	Licitatie deschisa		36000000.0

Source: generated by authors.

After generating these results, a request was made for the evolution of the suspicious contracts throughout 2020, starting from March, when the state of emergency was declared, until the end of the year. The results are presented in Figure 6 below:

Figure 6. Temporal evolution of suspicious contracts in the pandemic year 2020

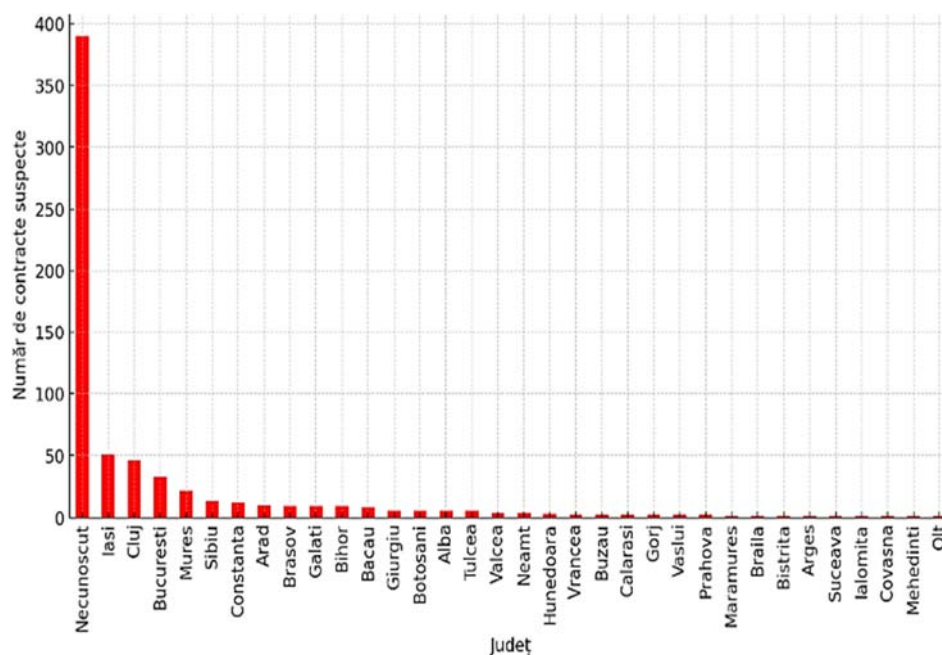


Source: generated by authors.

The results of the temporal analysis revealed that the peak of anomalies occurred in the period of March-April 2020, which may suggest that both algorithms based on artificial intelligence considered this to be due to purchases made during the emergency period, established in Romania from March 16, 2020, to May 15, 2020. Additionally, the graph indicates a significant decrease in anomalies starting from June 2020.

To see which counties had the highest number of suspicious contracts, an analysis was requested regarding all the identified contracts at the national level. Since the SEAP database did not have a separate column for the name of the county, the algorithm extracted this information from the name of the contracting authority (e.g., "Spitalul Județean de Urgență Pitești" → Argeș). However, this was not always possible, which led to the elimination of 390 cases where the contracting authority did not mention the county to which it belongs. The results are presented in Figure 7 below:

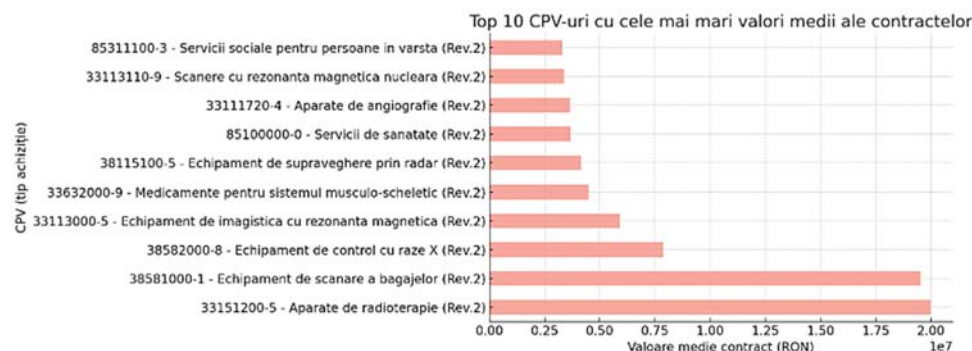
Figure 7. *Distribution of suspicious contracts by counties*



Source: generated by authors.

It can thus be observed that Iași (51 contracts), Cluj (46 contracts), and Bucharest (33 contracts) have the highest number of suspicious contracts. The other counties, which show fewer anomalies, are those that have carried out fewer high-value public procurements, exceeding 1.5 million RON.

Subsequently, the analysis of the database was extended by requesting an examination of potential anomalies by CPV category, in order to identify which types of products/services are more prone to risk. Additionally, these CPV code anomalies were correlated with the contracting authorities to determine whether the algorithms identify the awarding of suspicious contracts. The results are presented in Figure 8 below:

Figure 8. Top 10 CPV codes with the highest average contract values

Source: generated by authors.

From the data analysis presented in Figure 8 above, it can be observed that the highest average contract values are for medical and security equipment, namely radiotherapy machines (~20 million RON), baggage scanning equipment (~19.5 million RON), and X-ray control equipment (~7.8 million RON). Contracts for social services and healthcare also have high values.

Figure 9. Final Excel Database Containing Suspicious Contracts

	A	B	C	D	E	F	G	H	I	J	K
	Nr anunt atribuire	Denumire contract	Tipul contractului	Tip procedura	Cod si denumire CPV	Data publicare	Valoarea atribuita	Autoritatea contractanta	Valoarea atribuita scalata	Anomalie IF	Anomalie LOF
1	CAN1032486	Achiziție de echipamente de protecție	Furnizare	Negociere fără publicare prealabilă	33100000-1 - Echipamente med	03.06.2020	301.620.150	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	65.3359689	-1	-1
2	CAN1047208	Acord-Cadru ce are ca obiect achiziția	Furnizare	Negociere fără publicare prealabilă	33141625-7 - Truse de diagnostic	24.12.2020	107.310.000	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	23.1889547	-1	-1
3	CAN1046370	Acord-Cadru ce are ca obiect achiziția	Furnizare	Negociere fără publicare prealabilă	33141625-7 - Truse de diagnostic	14.12.2020	91.500.000	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	19.7596727	-1	-1
4	CAN1047204	Acord-Cadru ce are ca obiect achiziția	Furnizare	Negociere fără publicare prealabilă	33141625-7 - Truse de diagnostic	24.12.2020	82.500.000	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	17.8075198	-1	-1
5	CAN1033297	Acord-cadru pentru furnizarea de servicii	Furnizare	Negociere fără publicare prealabilă	33157400-9 - Aparate medicale	13.05.2020	72.083.910	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	15.5482086	-1	-1
6	CAN1043274	Soluții tehnice pentru dotarea Salii de	Furnizare	Licitatie deschisa	33100000-1 - Echipamente med	26.10.2020	66.505.680	4382458 - SPITALUL CLINIC SFANTA MARIA	14.3382577	-1	-1
7	CAN1047206	Acord-Cadru ce are ca obiect achiziția	Furnizare	Negociere fără publicare prealabilă	33141625-7 - Truse de diagnostic	24.12.2020	57.900.000	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	12.4716351	-1	-1
8	CAN1033813	Extindere sistem integrat teledagnostic	Furnizare	Negociere fără publicare prealabilă	33195000-3 - Sistem de monitorizare	31.05.2020	54.000.000	23410107 - COMPLEXUL MULTIFUNCTIONAL CARAIMAN	11.6257022	-1	-1
9	CAN1032817	Achiziție Echipamente de protecție	Furnizare	Negociere fără publicare prealabilă	33100000-1 - Echipamente med	02.05.2020	45.000.000	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	9.67354922	-1	-1
10	CAN1028656	Furnizare, instalare si amenajare spațiu	Furnizare	Licitatie deschisa	33113000-5 - Echipament de iradiere	17.10.2020	36.000.000	23410107 - COMPLEXUL MULTIFUNCTIONAL CARAIMAN	7.7213963	-1	-1
11	CAN1033153	Acord-cadru nr. 14045/03.04.2020	Furnizare	Negociere fără publicare prealabilă	33100000-1 - Echipamente med	09.05.2020	35.974.685	13633330 - Ministerul Transporturilor și Infrastructurii	7.71590532	-1	-1
12	CAN1033345	Acordul cadru nr. 14045/03.04.2020	Furnizare	Negociere fără publicare prealabilă	33100000-1 - Echipamente med	12.05.2020	35.974.685	13633330 - Ministerul Transporturilor și Infrastructurii	7.71590532	-1	-1
13	CAN1036446	Acord cadru de furnizare - Ventilatoare	Furnizare	Negociere fără publicare prealabilă	33157400-9 - Aparate medicale	01.07.2020	30.596.916	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	6.5494356	-1	-1
14	CAN1045095	Achiziție de Ventilatoare medicale	Furnizare	Negociere fără publicare prealabilă	33157400-9 - Aparate medicale	23.11.2020	28.163.139	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	6.02153506	-1	-1
15	CAN1032818	Achiziție echipamente de protecție	Furnizare	Negociere fără publicare prealabilă	33100000-1 - Echipamente med	02.05.2020	28.000.000	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	5.98614925	-1	-1
16	CAN1032821	Achiziție echipamente de protecție	Furnizare	Negociere fără publicare prealabilă	33100000-1 - Echipamente med	02.05.2020	27.912.500	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	5.96716999	-1	-1
17	CAN1047691	Acord cadru Dispozitive de protecție	Furnizare	Negociere fără publicare prealabilă	33157810-6 - Instalatie de otologie	31.12.2020	25.845.000	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	5.51871708	-1	-1
18	CAN1030983	Achiziție de camere de izolare cu presiune	Furnizare	Negociere fără publicare prealabilă	33100000-1 - Echipamente med	28.03.2020	24.600.000	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	5.24866925	-1	-1
19	CAN1017153	Furnizare de echipamente medicale	Furnizare	Licitatie deschisa	33100000-1 - Echipamente med	14.11.2020	24.572.274	25502860 - ADMINISTRATIA SPITALELOR SI SERVICIILOR MEDICALE	5.24265532	-1	-1
20	CAN1073277	Kituri de reactivi pentru extracție de	Furnizare	Licitatie deschisa	33696000-1 - Reactivi pentru	20.11.2020	24.066.500	4453144 - INSPECTORATUL GENERAL AL POLITIEI ROMANE	5.13294997	-1	-1
21	CAN1033243	Contract subsecvent nr. 14576/08.04.2020	Furnizare	Negociere fără publicare prealabilă	33100000-1 - Echipamente med	12.05.2020	20.636.000	13633330 - Ministerul Transporturilor și Infrastructurii	4.38885434	-1	-1
22	CAN1032174	Instalatie de tomografie	Furnizare	Licitatie deschisa	33151200-5 - Aparate de radioterapie	17.04.2020	19.980.000	4547125 - Institutul Oncologic Prof. Dr. I. Chiriacu Cluj-Napoca	4.24656408	-1	-1
23	CAN1032820	Achiziție Echipamente de protecție	Furnizare	Negociere fără publicare prealabilă	33100000-1 - Echipamente med	02.05.2020	19.162.500	39983313 - OFICIUL NATIONAL PENTRU ACHIZITII CENTRAL	4.06924353	-1	-1
24	CAN1018411	ENDOPROTEZARE	Furnizare	Licitatie deschisa	33183200-8 - Proteze ortopedice	09.07.2020	17.624.662	4278728 - SPITALUL JUDETEAN DE URGENTA BACAU	3.73567742	-1	-1
25	CAN1033271	Echipamente scanare bagaje de mână	Furnizare	Licitatie deschisa	38582000-8 - Echipament de control	08.05.2020	16.011.993	RO282425 - AEROPORTUL INTERNATIONAL AVRAM IANCU	3.38588003	-1	-1

Source: generated by authors.

To make the analysis complete, I requested that these suspicious contracts be exported as an Excel file for detailed analysis. The provided file contains 663 positions with award notices regarding public procurement contracts concluded by public entities in Romania in 2020, primarily for medical equipment, sanitary materials, and medicines. These 663

notices were extracted from the total of 7073 notices in the initial SEAP dataset, which was processed for analysis using AI-based algorithms. The results are presented in Figure 9.

Similar to the procedure presented earlier, this type of risk analysis in public procurement across various areas of public administration at the national level can be conducted by extracting Excel files from SEAP, processing them, and analyzing them with the help of artificial intelligence-based algorithms. In this way, it is possible to identify suspicious public procurement procedures, select them, and categorize them by county. Subsequently, these can be analyzed in terms of their presence within the Romanian Court of Accounts' Annual Activity Program and examined by its territorial structures.

5. Conclusions

In Romania, the implementation of artificial intelligence-based tools is still in its early stages within public sector institutions, although the digitalization process is fairly advanced at this level.

Regarding the risk analysis that can be carried out concerning the execution of external public audits in the area of public procurement, the use of artificial intelligence can be extremely beneficial for several reasons. However, there are also a number of drawbacks to using artificial intelligence-based tools. In this regard, a SWOT analysis can be conducted to assess the opportunity of using such tools, with the main conclusions presented in Figure 11 below:

Figure 11. *SWOT Analysis regarding the Implementation of Artificial Intelligence-Based Tools within Supreme Audit Institutions*



Source: generated by authors.

Advanced data analysis and predictive analytics are advantages of using artificial intelligence-based tools within supreme audit institutions. Given that the public sector holds vast amounts of data concentrated in large databases, artificial intelligence significantly contributes to automating the analysis of this data, while also identifying potential irregularities that could indicate corrupt activities.

Furthermore, by using artificial intelligence algorithms based on NLP (natural language processing), supreme audit institutions could be able to detect irregularities related to the tender documentation for public procurement contracts. For example, they could identify

the potential introduction of restrictive conditions that might limit competition between economic operators. Regarding the process of risk analysis and evaluation, the use of artificial intelligence for data visualization, as well as the opportunity for continuous and real-time monitoring of data and information related to the activities of audited entities, are key advantages.

All these considerations support the use of such tools in external public auditing carried out by supreme audit institutions, with the benefits of using them clearly outweighing the disadvantages.

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From bias to bid: AI and behavioural influences on the valuation of sports players

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Abstract. *This article aims to study the main criteria underlying the transfers of football players. It has been observed that performance is strictly related to the salary a player gets, but its market value can also vary depending on other aspects such as age or people's prejudices. The case study is based on a linear regression performed on 50 La Liga players for the 2024-2025 season. As a result, it was observed that the market value of the players is related to the number of goals, assists and their age.*

Keywords: player valuation, behavioural bias, sports economics, transfer market, artificial intelligence.

JEL Classification: D40, D83, D91, L83, L86.

1. Introduction

Over time, it has been noticed that the sports field, especially football, has evolved a lot, both in terms of player performances, but especially from a financial perspective. According to UEFA data, in the last 10 years both the expenses and the earnings made from player transfers have increased exponentially (Neri et al., 2021).

Each manager of a football team possesses a certain pragmatic reasoning, which has the role of making him achieve his objectives in a realistic manner and in relation to the dynamic environment in which his team performs. Every manager wants to have the best players in his own team in order to win as many trophies as possible, but for this to happen, very high transfer amounts are paid (Lopez Frias, 2016).

The transfers of football players have sparked a lot of controversy over time, from amounts that are far too high, to speculation based on bias.

Thus, this research aims to study what are the main factors that contribute to the increase in the market value of football players, but also how much performance criteria matter in the context in which football is currently considered a business.

2. Literature review

Studies show that players' remuneration is closely linked to the level of performance achieved by each player. The more goals a football player scores or provides valuable assists for his team, then his market value will increase and his salary will also become better. However, there is also the case when a club wants a player who is still under contract with another club. In this case, in addition to the transfer price established between the clubs, a transfer clause may also be charged, which has the role of compensating for the loss of productivity of the football player during the remaining duration of the contract (Ruijg and van Ophem, 2014).

If the transfer of a player was made for a very large amount, the coach has the opportunity to constantly monitor his performance. However, if the player performs below expectations, there are few cases in which the club can recover its investment. For this reason, the players' salary also includes numerous performance clauses, so if their level is high they will be rewarded accordingly, otherwise it can decrease (Poli et al., 2024).

Teams in Europe can usually get players in three ways, namely their own academy, players brought in free to contact or most commonly, by buying.

Also, the transfer market is greatly influenced by the fact that teams end up using certain players just because they have been paid very large amounts for them and they have to justify them. For example, Neymar's transfer in 2017 from FC Barcelona to PSG was a very big one from a tax perspective. PSG paid the amount of 222 million euros, which was a real record. This suggests how much transfer amounts have increased in recent years and continue to do so. Compared to the period of the 90s when a very good player was bought for the amount of 1-2 million euros, now this amount has become within the reach of many developed clubs (Hacking, 2019).

However, aspects related to technological evolution must also be taken into account, since both for training carried out at the highest level and for the transfer period, many clubs have begun to rely on digital technologies and incorporate artificial intelligence so that they can obtain the best data sets and choose the players who are at the highest parameters (Franceschi et al., 2024).

3. Methodology

In order to be able to study what influences the value of football players in the main Spanish football league, La Liga,

in the 2024-2025 season, a multiple linear regression was performed. The data for 50 players, having the positions of midfielder and striker were collected through the Transfermarkt website. Only those positions were used, because it was intended that the chosen variables were relevant in the context of the chosen footballers, and it was not applicable to investigate how many goals a defender or goalkeeper scored, because their main attributions have a defensive character. The dependent variable was "Market Value", and the independent variables were "age", "goals", "assists". The choice to divide the variables in this way was made starting from the desire to study the market value of the players and more precisely what can influence it. After data processing, the regression was performed using SPSS software. Among the tests performed are the Pearson correlation, the R^2 coefficient, the ANOVA test, t-tests for individual coefficients, collinearity diagnostics and Durbin-Watson.

The main hypothesis that has been researched is related to how much sports performance quantified in numbers, such as goals, assists, matters in relation to the age, image, popularity of the players or the prejudices to which they are exposed at certain times.

4. Results and discussions

The results obtained suggest that the model is statistically representative, more precisely the ANOVA test highlights this by $F = 33.232$ and $p < 0.001$. Also, through the coefficient R^2 , which has a value of 0.684, it results that the model explains around 68.4% of the variation in the market value of athletes. This is explained by the variables used, age, goals and assists.

Descriptive Statistics

	Mean	Std. Deviation	N
Market Value M€	32.260	44.6335	50
Age	25.50	3.908	50
Goals	7.28	6.919	50
Assists	3.82	3.237	50

Correlations

		Market Value M€	Age	Goals	Assists
Pearson Correlation	Market Value M€	1.000	-.231	.403	.570
	Age	-.231	1.000	.536	.036
	Goals	.403	.536	1.000	.146

	Assists	.570	.036	.146	1.000
Sig. (1-tailed)	Market Value M€	.	.053	.002	.000
	Age	.053	.	.000	.401
	Goals	.002	.000	.	.155
	Assists	.000	.401	.155	.
N	Market Value M€	50	50	50	50
	Age	50	50	50	50
	Goals	50	50	50	50
	Assists	50	50	50	50

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.827 ^a	.684	.664	25.8842	1.519

a. Predictors: (Constant), Assists, Age, Goals

b. Dependent Variable: Market Value M€

ANOVA^a

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	66795.493	3	22265.164	33.232	.000 ^b
Residual	30819.627	46	669.992		
Total	97615.120	49			

a. Dependent Variable: Market Value M€

b. Predictors: (Constant), Assists, Age, Goals

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	149.697	27.140		5.516	.000					
	Age	-6.831	1.122	-.598	-6.088	.000	-.231	-.668	-.504	.711	1.406
	Goals	4.200	.640	.651	6.561	.000	.403	.695	.544	.697	1.435
	Assists	6.850	1.156	.497	5.924	.000	.570	.658	.491	.976	1.024

a. Dependent Variable: Market Value M€

Collinearity Diagnostics^a

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	Age	Goals	Assists
1	1	3.332	1.000	.00	.00	.02	.03
	2	.380	2.960	.00	.00	.48	.45
	3	.279	3.454	.02	.01	.25	.50
	4	.009	19.700	.98	.99	.25	.01

a. Dependent Variable: Market Value M€

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-19.481	167.301	32.260	36.9212	50
Residual	-45.4443	76.3649	.0000	25.0793	50
Std. Predicted Value	-1.401	3.658	.000	1.000	50
Std. Residual	-1.756	2.950	.000	.969	50

a. Dependent Variable: Market Value M€

The regression highlights the correlation between the market value of the players and their level of performance on the field, such as goals, assists, but also takes into account the age of each player, because in most cases, it has been observed that with age, their football

level decreases. There are of course exceptions, such as Cristiano Ronaldo, Lionel Messi or Robert Lewandowski, players who, despite their age, continue to perform at a high level.

On the other hand, when a player is transferred, biases can also occur, as was the case with Gareth Bale, who in the 2012-2013 season was transferred from Tottenham to Real Madrid for €100 million. At the time, this transfer was harshly criticized by the Spanish population, because Spain was going through a great financial crisis, the unemployment rate was about 28% and many harsh fiscal policies were adopted with the population, which led to a budgetary austerity felt by most of the individuals living in Spain. The transfer fee sparked indignation, because while many people were no longer able to have an income, Real Madrid paid a colossal amount for a very good player, who from the perspective of performance, had all the data on his side, but nevertheless, compared to that context, people were biased, since their own problems had priority to the detriment of a football transfer (Lopez Frias, 2018).

Currently, more and more clubs are turning to video analysis of players based on artificial intelligence. This is achieved by the fact that each player is monitored from the perspective of physical parameters, both in training and during official games. By involving artificial intelligence in this aspect, football coaches have data sets interpreted in detail and reported at every moment from training or from the official match. It is a good way to see which players respond well to certain playing techniques or in the case of others, it is to watch how they recover after a difficult injury and how long it can be estimated that the player will be able to return to the field (Zaytseva and Shaposhnikov, 2022).

This research has its own limitations, from the perspective of the selected variables, but can be used in the future for a more elaborate study on this broad and interesting field, such as the football player transfer market.

5. Conclusions

In conclusion, the transfer market of football players is a very dynamic one, which has evolved a lot in the last ten years. This is largely due to the investments that have been made in this field and because more and more entrepreneurs choose to invest in football teams, seeing them as profitable businesses.

Also, the main factors that influence the transfer of a football player is his level of performance, but it is not neglected that there may be certain behavioural biases, which when put under pressure from a critical public, can lead to the price of a player to decrease, increase or in an extreme case, that transfer no longer takes place.

Following the linear regression performed, it was found that variables such as the number of goals, assists or age are important factors that influence the market value of players. Thus, for a strong championship such as Spain's, 50 players with an offensive profile were analysed to correspond to selected variables.

The market for transfers of football players is one with high potential, and the influence of artificial intelligence leads to the desire of clubs to be as well informed as possible when they choose to buy a certain player.

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Artificial Intelligence: the catalyst for new industrial revolution and economic development?

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Abstract. *Research-development-innovation drives economic growth and competitiveness. AI, a key element of Industrial Revolution 4.0 (transitioning to 5.0), transforms industries and society, offering innovation but also risks. This study reviews AI's role as a catalyst for industrial and economic change. Using multiple regression on EU27 data (2017–2022), it examines factors influencing "AI software development - Very High-impact AI projects (%)". The tested hypothesis states that talent availability and R&D investments shape AI project scope. Independent variables include R&D expenditure, venture capital in AI, researcher count, and the global innovation index. Results confirm that AI development depends on these factors. The findings provide insights for policymakers and industry leaders, highlighting the need for regulations to manage risks. Future research should address AI governance and long-term effects.*

Keywords: AI projects, investments in AI, R&D, Global Innovation Index, researchers in R&D.

JEL Classification: O33, O38, C23, L86, M15.

1. Introduction

Technological changes play an essential role in stimulating investments and driving economic growth (Romer, 1990; Aghion & Howitt, 1992). In turn, the ensemble of artificial intelligence (AI) technologies plays an essential role in the modern industrial revolution, bringing intelligent solutions that transform various sectors of activity. On the other hand, in the last decade, the significant economic and social impact of AI has led governments and international organizations to pay increased attention to regulating this field to balance benefits with associated risks, specifically the results of technological innovation with the protection of fundamental rights and ensuring security.

AI is an interdisciplinary field dedicated to developing systems capable of performing tasks specific to human intelligence. Its first documented appearance was in 1956. Since then, AI has evolved significantly, having a major impact on industry and society (Howard, 2019; Jutel et al., 2023).

On the other hand, the United States, China, and the European Union, which are the main actors in the global governance of artificial intelligence, have distinct priorities. China emphasizes "research and application," the European Union focuses on "social impact," and the United States on "the role of government," but all three powers underscore the importance of institutions, respect for human rights, and promotion of scientific research (Wang et al., 2025). Managing AI challenges requires strengthened international cooperation, and the concept of "technological diplomacy" is proposed as a tool for aligning policies at the global level (Feijóo et al., 2020).

Given the trend of AI-aided development, the European Union will need to adopt strategic measures to support and accelerate the integration of AI in all sectors of sustainable development and strengthen its competitive position in the global market.

In the study, we will answer the research question derived from the paper's title. At the same time, in this period of digital and technological momentum, the present study focuses on the main determinants of AI projects at the level of EU member states. Through the multiple regression approach, our research aims to identify the impact of relevant predictors on the level of very high-importance AI projects.

2. Literature review

Industrial Revolution 4.0, a concept popularized by the founder of the World Economic Forum, Schwab (2016), describes an era in which advanced technologies merge to fundamentally transform society and the global economy. This revolution is characterized by the convergence of digital, physical, and biological technologies, having a significant impact on all economic and social sectors (Anderson, 2016; Li et al., 2017; Schiølin, 2020). These technologies include: *digitalization and hyperconnectivity* as a result of the central role of data (Bianchi & Labory, 2018), *Internet of Things (IoT)* which connects devices and machines for intelligent automation facilitating production processes (Xu, H., et al., 2018; Martinelli et al., 2020), *Artificial Intelligence (AI) and Machine Learning (ML)* optimize processes and facilitate advanced automation, for example autonomous vehicles and virtual

assistants (Ross & Maynard, 2021) being essential in decision-making and reducing dependence on human intervention (Syam & Sharma, 2018), *Big Data and Cloud Computing* which allow analysis, scalability and efficient storage of data for informed decisions, along with inherent challenges and risks (Sandhu, 2021), *advanced robotics, industrial automation and wireless communication techniques* that increase efficiency and reduce production costs (Martinelli et al., 2020, Imran et al., 2020), *additive manufacturing* (3D printing) which supports product customization and production sustainability (Mohamed et al., 2024). All these technologies have a significant impact on how industries are managed and operated.

Industry increasingly dominates AI research, having control over computing power, large datasets and benefiting from the contribution of qualified researchers (Ahmed et al., 2023). AI is integrated into various fields, including healthcare, circular economy, supply chains, and management (decision-making), having a significant impact on business, social sciences, and exact sciences (Dwivedi et al., 2023).

The transition from Industry 4.0 based on digitalization, to Industry 5.0, represents an evolution based on the principles of the previous industrial revolution, plus personalized products, advanced communications, collaborative robots, new technologies – artificial intelligence of things (AIoT), with the main objective of production sustainability (Xiang et al., 2024), the approach being viewed from multiple perspectives - economic, ecological, and social. The last two perspectives require the adoption of a circular economy and orientation toward a human-centered industry (Möller et al., 2022). At the same time, from the specialized literature we also note that the transition to Industry 5.0 involves: *human-machine collaboration*, with emphasis on human integration and sustainability (Xu et al., 2018; Möller et al., 2022), *smart cities* through the development of autonomous and connected infrastructure (Ross & Maynard, 2021) and *renewable energy solutions* to reduce the negative impact on the environment (Mohamed et al., 2024).

Technological Impact of AI: Artificial intelligence (AI) is an essential factor of Industry 4.0, revolutionizing production processes and industrial design, contributing to automation and optimization, which leads to increased efficiency and reduced costs (Javaid et al., 2021; Malik et al., 2024). On the other hand, the integration of AI and robotics in high-precision tasks is revolutionizing the manufacturing industry, medicine, and agriculture. Thus, AI-based robotic systems, using advanced algorithms, machine learning, and real-time sensor data, achieve superior levels of precision, efficiency, and adaptability (Paköz, 2024). The development of self-learning and self-coding algorithms, recurrent neural networks (RNN), reinforcement learning, and pre-trained models are key aspects of AI progress in the last decade (Shao et al., 2022). As such, AI has the role of amplifying human activities and making us more efficient.

Technological Impact of AI on the Economy and Competitiveness: Investments in AI stimulate productivity, sales, employment, and company value through product innovations (Babina, et al., 2024). Additionally, AI stimulates innovation and influences productivity through task automation, simplifying operations, and reducing costs (Yi & Ayangbah, 2024; Chaudhary, 2024). AI contributes to economic growth in countries with strong national strategies and advanced infrastructure (Huy, et al., 2024), being essential in

emerging economies (Fan & Liu, 2021). On the other hand, to maximize the benefits of AI, it is necessary to integrate this technology in emerging fields to enhance competitiveness (Shao, et al., 2022), as well as in governance systems (Saba & Ngepah, 2024). At the same time, to stimulate AI capacity, collaboration between the public sector, private industry, and educational institutions is important (Ozkaya & Demirhan, 2023). Artificial intelligence (AI) projects have a significant impact on economic growth, influencing productivity, innovation (Yuan et al., 2024), as well as the structure of the labor market, with the effect on the latter being bivalent. Thus, some jobs disappear, new, more qualified work tasks appear due to automation, but the replacement rate is slower; moreover, a slower increase in productivity compared to previous decades is also observed. Government correction measures are necessary in this context, as well as adjusting the educational curriculum in accordance with the new requirements of the labor market (Acemoglu & Restrepo, 2019). Artificial intelligence can be both an initiator and a facilitator of innovation, supporting the creation of new products and accelerating progress in the innovation process (Brem et al., 2021). AI projects are essential for economic development. Coherent national strategies and measures to combat AI risks are important for strengthening a nation's competitive advantage in the global market.

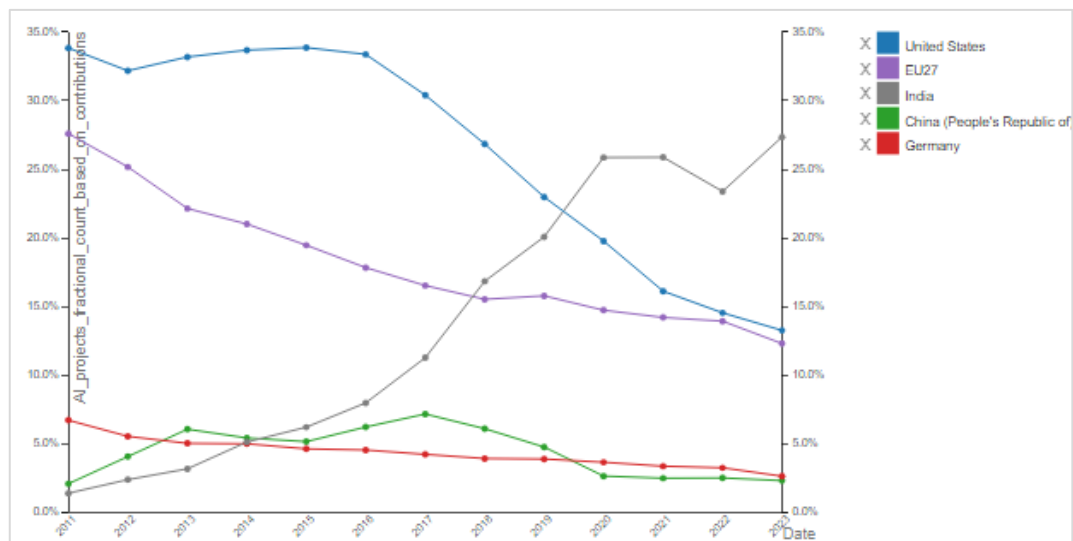
Impact of Research and Development Expenditures on AI Projects: The financial success of companies is due to focusing on AI technologies and increased R&D investments (Kumari et al., 2024), and revenues increase where the intensity of AI technology adoption is higher (Lee et al., 2022). R&D investments, especially when combined with AI, can enhance researcher productivity, accelerating the growth of innovations and implicit economic growth (Besiroglu et al., 2022). Conversely, AI promotes technological innovation by accelerating knowledge creation and technology transfer, improving learning capabilities, and increasing investments in R&D and talents (Liu, et al., 2020). At the same time, companies with intense R&D activities are more likely to adopt AI technologies (Kinkel, et al., 2021). The study by Xiao et al. (2024) shows that enterprises that adopt AI increase their R&D activity efficiency and performance indicators (revenue and market share).

Consequently, expenditures in research and development (R&D) oriented toward artificial intelligence (AI) projects can have a positive impact on development, technological innovation, and technological and financial progress.

Impact of the Number of Researchers vs. AI: Al-Marzouqi & Arabi (2024) found that global AI research has grown 26 times in 25 years, with China leading in publications and India showing rapid growth. While India ranks first in researcher count and R&D spending, Hong Kong and Singapore excel in top-tier journals, and Switzerland leads in citations per article. After normalizing indicators, Hong Kong, Singapore, and Switzerland, along with the USA, showed the highest economic impact via patent citations. The study suggests that AI impact depends not just on the number of researchers but on research quality, specialization, and applicability.

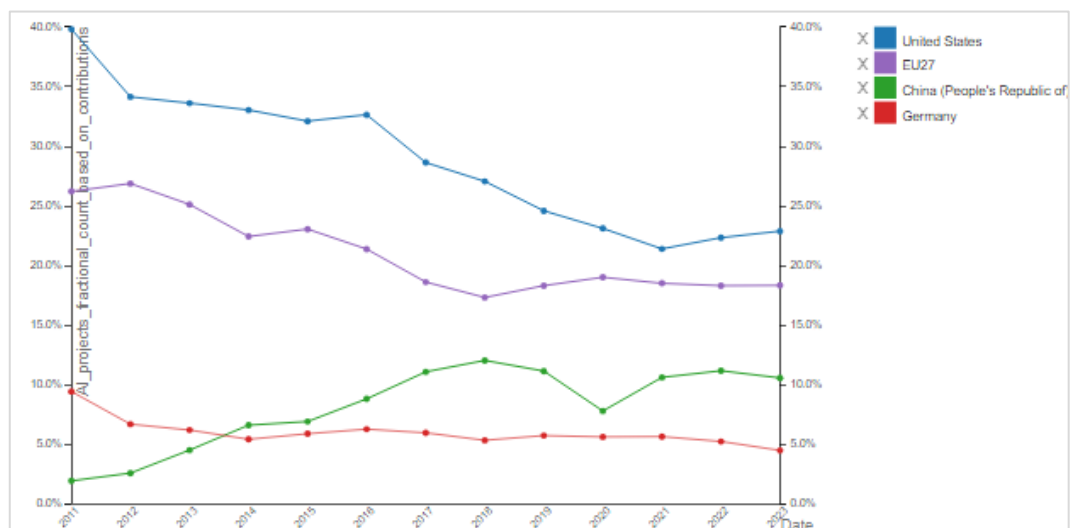
On the other hand, from OECD information, high-impact AI projects (6-100 forks, Fig. 2) and very high-impact projects (>100 forks, Fig. 3) bring to the forefront the USA, China, and the EU. India scores in quantity in total AI projects (Fig. 1), but we can infer from the figures presented that Indian AI projects are of a smaller scale.

Figure 1. AI software development. Contributions to public and project impact. ALL AI projects (%)



Source: OECD.AI

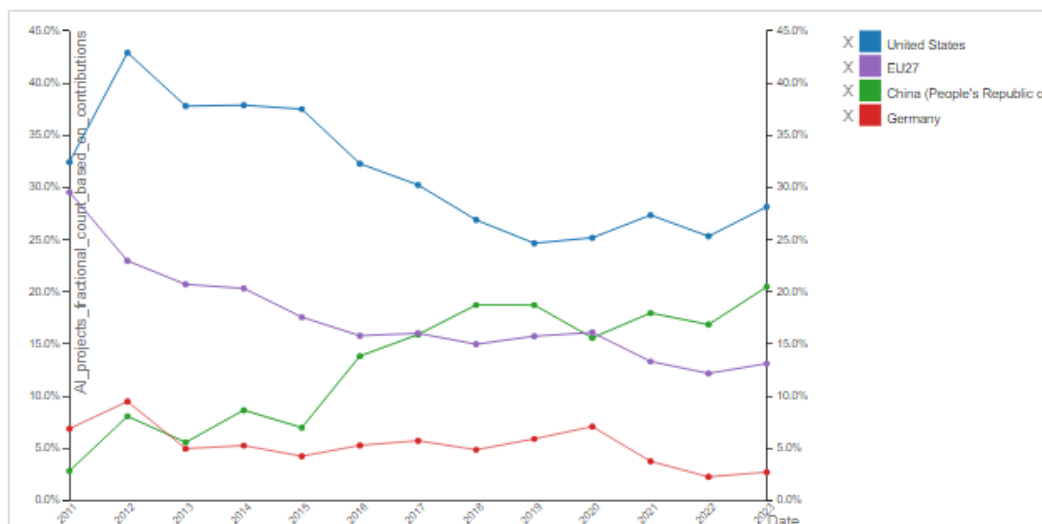
Figure 2. AI software development. Contributions to public and project impact. High-impact (6-100 forks) AI projects (%)



Source: OECD.AI

We take note from Fig. 2 that the EU occupies a reasonable position around high-impact AI projects (6-100 forks). We cannot note the same thing around very high-impact AI projects (Fig. 3).

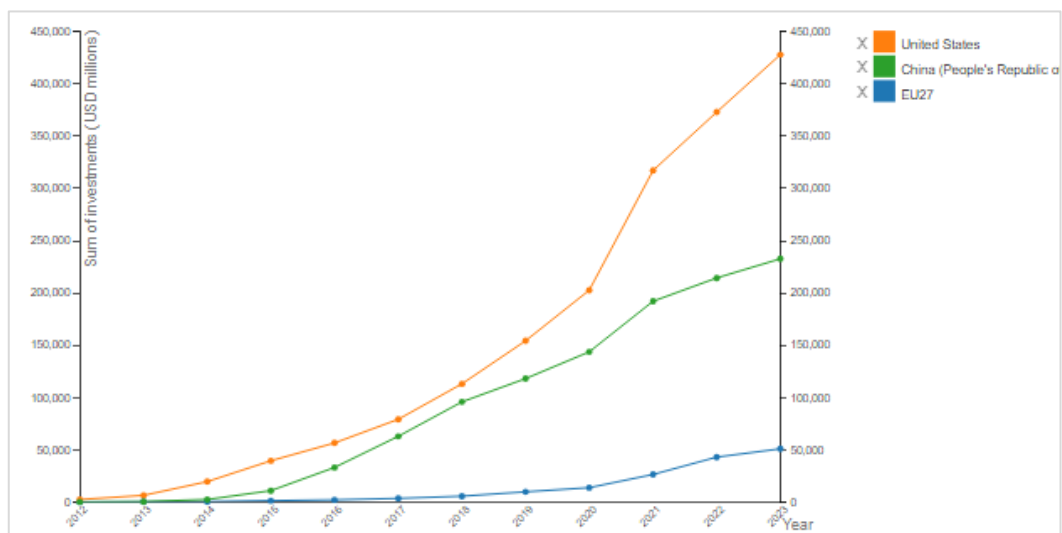
Figure 3. AI software development. Contributions to public and project impact. Very High-impact (>100 forks) AI projects (%)



Source: OECD.AI

These charts show the number of AI projects (i.e., AI-related GitHub 'repositories') as a fractional count based on the share of contributions (i.e. 'commits') by country and over time.

Figure 4. Venture capital investments in AI, sum of investments (USD million)



Source: OECD.AI

About the Venture capital investments in AI indicator (see Fig. 4), the USA holds supremacy with 427 billion USD, followed by CHINA with 232 billion USD, representing the aggregate amounts over the last 11 years (2012-2023). For this indicator, the EU in total aggregate value reaches only 50.8 billion EUR, far behind the main competitors.

3. Methodology

In this study, we used two research methods:

- Systematization of relevant literature (described in section 2) and
- Empirical analysis based on data, statistical methods, and techniques to test the working hypothesis H1: Available talent and the level of investments in research, development, and innovation significantly influence the scope of AI projects.

Specifically, the quantitative analysis consists of:

Multiple regression, to figure out the direction of relationships and connections between AI projects and their predictors

- Data used: Eurostat, OECD.ai, World Bank, IMD World Competitiveness
- Analysis period: 2017-2022. Number of observations = 28 (27 EU member states plus the EU average)

Definition of the model and variables subject to analysis:

The multiple regression equation is expressed by the formula below:

$$(AI_projects)_i = \beta_0 + \beta_1(RD_GDP)_i + \beta_2(VC_Invest)_i + \beta_3(Researchers)_i + \beta_4(GII)_i + \varepsilon_i \quad (1)$$

where:

The dependent variable (acronym/name) is: AI_Very High Impact/AI software development. Very High-impact (>100 forks) AI projects (%) (Source: OECD.ai).

Independent variables (predictors) are described in Table 1 (p. 9).

β_0 = intercept, $\beta_1 \div \beta_4$ are regression coefficients, and ε is residual error.

Statistical Methods and Techniques Used in Our Analysis:

- *Data Preparation and Cleaning.* We employed two approaches to handle predictors' missing data: calculating the average values (arithmetic mean neighboring values) and, in certain cases, utilizing Python-based predictive models for data imputation (linear regression or polynomial regression technique). EU-level values were calculated as weighted averages based on either population or GDP, depending on the case. • *Data scaling/normalization (Z-score or min-max scaling).* In this case, we applied standard normalization (Z-score), which transforms the data so that: Mean = 0 and Standard Deviation = 1. This allows the comparison of variables with different units on the same scale.
- *Preliminary Factor Analysis.* KMO Test (Kaiser-Meyer-Olkin) for measuring sampling adequacy (in other words, to evaluate the internal consistency of the selected variables).

In theory, the KMO value must be between 0.5 and 1 (i.e., above 50%), indicating adequate sampling.

- *Multicollinearity Analysis.* To address the issue of multicollinearity and obtain more robust results, we applied the following solutions in our analysis: calculating the Variance Inflation Factor (VIF) and, when necessary, implementing regularization methods. In general, a VIF below 10 (preferably below 5) does not indicate severe multicollinearity issues. If $VIF > 10$, the appropriate regularization technique is applied: Ridge Regression, Lasso Regression, or Elastic Net (average between Ridge and Lasso).
- *Correlation Analysis.* This is a statistical technique that allows measuring the degree of interdependence between 2 studied variables and their statistical significance. To evaluate the intensity of relationships between variables, we used Pearson correlation coefficients (theoretical range: 0 – 1, preferred range: 0.50 – 0.95).
- *Regression Analysis.* In our case, multiple linear regression analysis. Regression analysis studies the relationship between the dependent variable and the rest of the independent variables, also called explanatory variables or predictors. The most important results of regression analysis are the R coefficients, R Square (R^2), and the statistical significance level. In regression analysis, the coefficient of determination (R^2) is crucial as it shows that the independent variables explain the percentage of variation in the dependent variable. The statistical significance should ideally be below 0.05, indicating over 95% confidence. In current practice, values up to 0.1 are also accepted.
- *Analysis of Variance (ANOVA).* In our case, multifactorial ANOVA is a statistical method that helps study the impact of explanatory factors on the dependent variable to certify the statistical significance of the model (< 0.05).
- *Validation and Interpretation of Results*

Table 1. The independent variables selected in the analysis and their impact on the AI domain

Independent Variable (acronym)	What it measures?	Relevance of the variable	Data source
1. Total expenditure for R&D, as percentage of GDP (R&D%GDP)	Measures the level of investment in research and development, % of GDP	R&D investments are essential for technological innovation, including AI development. Countries with high R&D expenditures tend to have more successful AI projects	World Bank & EUROSTAT
2. Venture capital investments in AI (VC_Invest_AI), % of GDP (VC_invest AI)	Measures the level of funding for companies developing AI technologies, % of GDP	This type of funding supports the development of AI projects and can influence the number of high-impact projects	Calculated by the authors based on OECD.ai data for the indicator Venture capital investments in AI, expressed in USD millions by country, as well as World Bank statistics for GDP values expressed in constant 2015 prices, USD millions
3. Total number of researchers in R&D per million people (Researchers)	Measures the density of researchers involved in R&D activities per 1 million inhabitants	A country with many researchers has the critical mass necessary to form a qualified workforce capable of generating innovations and contributing to successful AI projects	WORLD BANK (via UNESCO)
4. Global Innovation Index (GII), overall score: [0;100]	Measures the innovative ability and performance of countries	Countries with a higher GI score usually have more human resources (talents) and adequate infrastructure to support research and development, including in AI	WIPO

Source: authors' elaboration, March 2025.

4. Results and discussions

Research Question: Could Artificial Intelligence (AI) be considered a catalyst for a new industrial revolution and economic development?

Answer: Following the systematization of relevant literature, the majority opinion is that AI enables automation and optimization of repetitive and complex processes, reducing costs and increasing efficiency and labor productivity. Moreover, robots and intelligent algorithms can replace or aid human labor in sectors such as industry, logistics, and services (finance, education, and health). AI will drop repetitive jobs but will generate (at a slower pace, according to Acemoglu) new jobs in areas such as algorithm development, AI ethics, and cybersecurity. Of course, professional retraining measures are necessary. The answer to the research question is that AI is a vector of the new industrial revolution, but its full success will depend on regulation, adequate education, and the adaptability of the labor market to new requirements.

For testing the statistical hypothesis H1, we present below the results of the empirical analysis: Kaiser-Meyer-Olkin (KMO) Test Results: Overall KMO Value: 0.6287 (62.9% shows moderate suitability for factor analysis).

VIF < 10 for all predictors. Regularization of coefficients is not needed, so we will proceed directly to correlation and regression analysis.

Table 2. *Correlation matrix 2017*

Variables	AI_Very High Impact	VC_Invest AI	R&D %GDP	Researchers	GII
AI_Very High Impact	1	0.6532	0.4287	0.3245	0.3102
VC_Invest AI	0.6532	1	0.2934	0.1876	0.1945
R&D %GDP	0.4287	0.2934	1	0.8456	0.6712
Researchers	0.3245	0.1876	0.8456	1	0.7234
GII	0.3102	0.1945	0.6712	0.7234	1

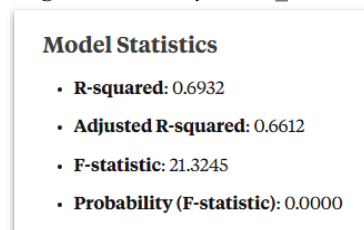
Source: authors' elaboration, March 2025

Table 3. *Regression Coefficients Table 2017*

Variable	Coefficient	Standard error	t-statistic	p-value
Intercept	-0.0002	0.0876	-0.0023	0.9982
VC_Invest AI	0.3876	0.1132	3.4238	0.0014
R&D %GDP	0.2654	0.1054	2.5183	0.0156
Researchers	0.1432	0.0965	1.4838	0.1456
GII	0.0765	0.1187	0.6445	0.5231

Source: authors' elaboration, March 2025

Figure 5. *Summary Model_2017*



Source: authors' elaboration, March 2025

Table 4. ANOVA Results 2017

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-statistic	p-value
Regression	8.1243	4	2.0311	21.3245	0.0000
Residual	3.5678	36	0.0991	-	-
Total	11.6921	40	-	-	-

Source: authors' elaboration, March 2025.

Correlation Highlights (see Table 2):

- Moderate positive correlation between AI Impact and VC Investments (65,32%)
- Weak positive correlation between AI Impact and R&D %GDP (42,87%)
- Strong positive correlation between Researchers and R&D %GDP (84,56%)
- Moderate positive correlation between Researchers and GII (72,34%)
- Moderate positive correlation between R&D %GDP and GII (67,12%)

Regression Analysis & Model Performance (see Table 3 – 4 and Fig. 5):

- VC Investments in AI remain the most significant predictor ($p = 0.0014 < 0.01$)
- R&D Expenditures also significant ($p = 0.0156 < 0.05$)
- **The model** explains 69.32% of AI Impact variance
- Globally significant model ($p = 0.0000$)

Table 5. Correlation matrix 2022

Variables	AI_Very High Impact	VC_Invest AI	R&D %GDP	Researchers	GI
AI_Very High Impact	1	0.7624	0.5203	0.4118	0.3946
VC_Invest AI	0.7624	1	0.3782	0.2647	0.2519
R&D %GDP	0.5203	0.3782	1	0.8234	0.6571
Researchers	0.4118	0.2647	0.8234	1	0.7312
GI	0.3946	0.2519	0.6571	0.7312	1

Source: authors' elaboration, March 2025.

Kaiser-Meyer-Olkin (KMO): Test Results Overall KMO Value: 0.6542 (65,4% indicates moderate suitability for factor analysis).

VIF < 10 for all predictors. The regularization of coefficients is not required.

Table 6. Regression Coefficients Table 2022

Variable	Coefficient	Standard error	t-statistic	p-value
Intercept	-0.0001	0.0892	-0.0013	0.9990
VC_Invest AI	0.4237	0.1154	3.6721	0.0009
R&D %GDP	0.2918	0.1076	2.7120	0.0095
Researchers	0.1654	0.0987	1.6753	0.1022
GI	0.0932	0.1243	0.7496	0.4578

Source: authors' elaboration, March 2025.

Figure 6. Summary Model_2022

Model Statistics

- **R-squared:** 0.7243
- **Adjusted R-squared:** 0.6923
- **F-statistic:** 22.4568
- **Probability (F-statistic):** 0.0000

Source: authors' elaboration, March 2025

Table 7. ANOVA Results 2022

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-statistic	p-value
Regression	8.4521	4	2.1130	22.4568	0.0000
Residual	3.2198	36	0.0894	-	-
Total	11.6719	40	-	-	-

Source: authors' elaboration, March 2025

Correlation Highlights (see Table 5):

- Strong positive correlation between AI Impact and VC Investments (76,24%)
- Moderate positive correlation between AI Impact and R&D %GDP (52,03%)
- Moderate positive correlation between Researchers and GII (73,12%)
- Strong positive correlation between Researchers and R&D %GDP (82,34%)
- Moderate positive correlation between R&D %GDP and GII (65,71%)

Regression Analysis & Model Performance (see Table 6 – 7 and Fig. 6):

- VC Investments in AI remain the most significant predictor ($p = 0.0009 < 0.01$)
- R&D Expenditures are also significant ($p = 0.0095 < 0.01$)
- **Weak predictor: Researchers ($p = 0.1$, indicating 90% confidence)**
- The model explains 72.43% of AI Impact variance
- Globally significant model ($p = 0.0000$)

5. Conclusions

The current industrial revolution, known as Industry 4.0 (evolving towards Industry 5.0), is characterized by advanced technologies that profoundly modify current socio-economic and industrial systems, with AI occupying an important place in these transformations.

On the other hand, AI projects are essential for enhancing national competitiveness, having a significant impact on technological and economic capabilities. Strengthening the competitive advantage of organizations and implicitly of nations in the global market requires integration of scientific knowledge, development of appropriate national strategies, and addressing challenges specific to artificial intelligence.

Artificial Intelligence (AI) can be considered a catalyst for socio-economic progress and the new industrial revolution, but its full success will be conditioned by an efficient regulatory framework and an adequate educational system capable of adapting to new labor market requirements.

Although this paper did not aim to address the risks associated with AI (unethical use, loss of low-skilled jobs, amplification of social inequalities, and loss of control), these will require special attention from legislators through regulation and strict control.

The results of the empirical analysis indicate that the development of very large-scale artificial intelligence projects is closely correlated with the level of investment in research and, especially in AI, while the influence of the total number of active researchers in the research and development (R&D) sector is lower. Intuitively, it can be argued that the

essential difference is determined by the quality and expertise of researchers rather than their number. Moreover, according to the latest available data, countries best positioned in the area of very important AI projects (Fig. 3) have, according to WB statistics (via UNESCO), a total number of researchers working in the R&D sector, per 1 million inhabitants, of approximately 4,500 (USA) and 1,700 (China), compared to countries at the top with 9,100 (Korea) or > 8,000 (Sweden), and India with only 260 researchers, which is a leader in small projects (Fig. 1 – ALL AI projects).

The multiple regression econometric model proposed in the empirical analysis is valid, and the dependency hypothesis, "Available talents and the level of investment in research, development, and innovation significantly influence the scale of AI projects," has been confirmed by the statistical results obtained.

The results of this study contribute to an in-depth understanding of the determinants of the development of artificial intelligence projects with significant impact at the level of EU27 member states. In this context, countries that allocate substantial financial resources in the field of research, development, and innovation, especially in the sphere of artificial intelligence, can anticipate considerable economic benefits. At the same time, the European Union cannot afford the risk of losing the global technological competition with its main rivals, the USA and China, especially in terms of progress in the field of artificial intelligence.

To strengthen its position in the field of artificial intelligence and increase its global competitiveness, the European Union should adopt a series of strategic measures:

- Increasing R&D Investments: Allocate more funds for AI projects through dedicated programs and encourage public-private partnerships for innovation.
- Fostering a Competitive AI Ecosystem: Promote collaboration between universities, research institutes, and industry to accelerate knowledge and technology transfer.
- Creating a Supportive Legal Framework: Implement clear, flexible regulations that foster innovation while safeguarding ethics and rights in AI use.
- Enhancing Digital Skills: Boost workforce competitiveness by offering educational and training programs for AI specialists.
- Supporting Start-ups and SMEs: Improve access to financing and markets for AI companies to enhance their global competitiveness.
- Building Advanced Digital Infrastructure: Develop high-performance computing networks, cloud infrastructure, and shared AI databases.
- Promoting International Cooperation: Establish strategic alliances to access advanced technologies and make a contribution to the development of global AI standards.

Regarding the study's limitations, future research may consider, but is not limited to, the inclusion of additional indicators and/or countries, the examination of longer periods (depending on data availability), the exploration of risks associated with digitalization and AI, along with strategies for their mitigation or elimination, and the formulation of new hypotheses or research questions related to the topic.

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The impact of Artificial Intelligence on job roles and innovation

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Abstract. *The evolution of society has rapidly increased over the past century. Due to the advancements of the industries that constitute the foundations of today's society we are currently at the highest rate of evolution in history. One of the most important tools that is in an early stage is Artificial Intelligence (AI). It has been one of the most transformative technologies of the 21st century, bringing profound changes to industries and job roles across the globe with minor and major impact over various sectors. This paper will evaluate the scope and introduction of AI tools in society and its impact over time.*

Keywords: Artificial Intelligence, evolution, society, technology, job.

JEL Classification: J23, J24, O33.

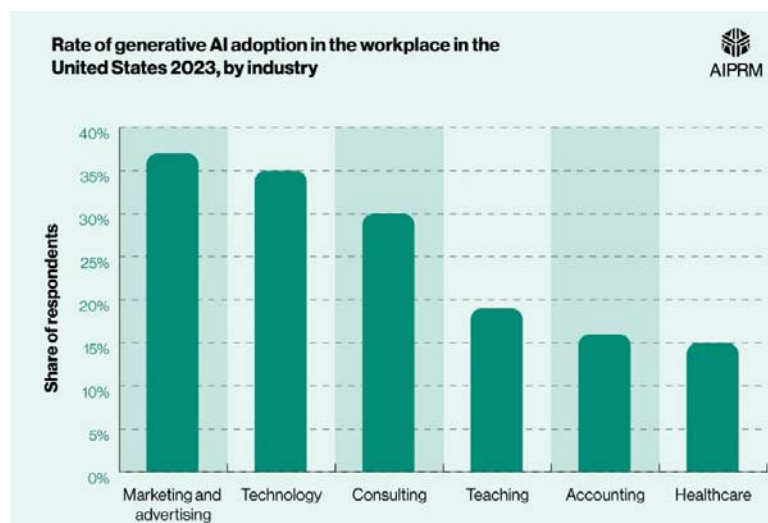
Introduction

Artificial intelligence has resulted in greater automation across different industries, significantly affecting jobs that entail repetitive or routine tasks. Fields like manufacturing, logistics, and clerical work have experienced a transformation as AI-driven systems undertake tasks with enhanced efficiency and accuracy. For example, robotic systems have taken over assembly line positions, allowing for continuous operation without errors, which has diminished the need for manual labor. This transition not only boosts productivity, but also lowers operational costs for companies, providing them with a competitive edge.

Nevertheless, this automation presents a challenge for the workforce, potentially causing job displacement. Employees in industries that heavily depend on routine activities face the risk of being substituted by machines, resulting in unemployment and the need for career changes. As a reaction, there's a growing demand for upskilling and reskilling activities to assist specialists adjust to modern parts that require human inventiveness, enthusiastic insights, and complex problem-solving capabilities.

The Path of New Opportunities

Numerous analysts share the vision that, within the labor markets of long-term , AI will substitute a much higher number of specialists compared to past automated technologies. This is often supported by the contention that (pre-AI) advanced computerization is routine-biased, replacing routine errands that take after a well-defined programme which can be codified and performed consequently based on calculations. Expert conclusion attests that AI innovations are planned to be skill-biased, meaning they illustrate human aptitudes such as coordinating, expectation, recognition, and cognition, which were, as it were as of late, broadly thought to be non-automatable (Özkiziltan, 2021).



(Statista, 2023)

AI has created opportunities for new job roles. The development, implementation, and maintenance of AI systems require specialized skills in data science, machine learning, and AI ethics. These emerging fields offer promising careers for those with the aptitude to learn and adapt to the rapid technological changes. Furthermore, AI has led to the creation of hybrid roles, where human oversight of AI systems is essential, combining technical skills with domain expertise.

AI also fosters innovation, encouraging professionals to engage in creative and strategic roles. It liberates human workers from mundane tasks, enabling them to focus on activities that require innovation and strategic thinking. As AI systems handle data entry and processing, marketers can concentrate on crafting creative campaigns, and engineers can design cutting-edge technologies.

Obstacles of AI adoption in the workforce

Analyzing the historical work methodology trends we can learn that the adoption and implementation of various technologies has not always been fast and permissive, but rather slow and inconsistent. Due to the slow rate of adapting to technology, by 2024 only 12% of workers in specific sectors report that they use AI to work on a daily basis. Historical changes have shown us that due to factors like cultural or different political applications to unclear business values or concerns related to trust, change at a macro level has always been a process.

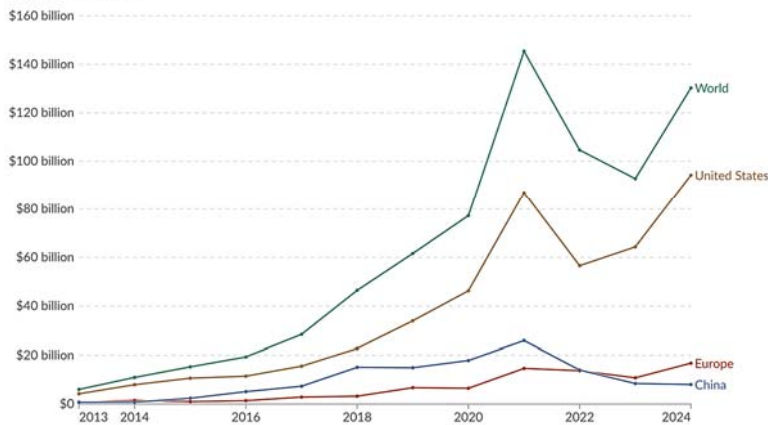
Trust is a vital element that needs to be addressed when adopting new technologies. To cultivate trust and support the ethical implementation of AI, there is a growing need for transparency and responsible use. More organizations are embracing responsible AI principles to enhance trust in decision-making processes by boosting explainability and reducing risks. Across both national and international levels, various regions are tightening regulations on AI to foster trust and ethical practices by defining clear limits and ensuring accountability. An example of this is the European AI Act, which incorporates the “human-in-the-loop” principle, highlighting human responsibility in decision-making. This principle could contribute to increased trust in AI by establishing accountability and honoring human values (Till Leopold, 2024).

Business Values

Some businesses are increasingly investing significant resources into AI technologies, with expectations of a 60% increase in AI investments over the next three years, potentially reaching 7.6% of IT budgets by 2027. Conversely, others are more hesitant, questioning the certainty of the returns that these investments may provide. Many companies frequently point to costs as a major obstacle to AI adoption, with several expressing uncertainty about the potential advantages of the technology. This doubt is heightened by the scarce evidence regarding the effect of AI on company performance. Initial results appear promising, but the definitive benefits remain ambiguous. For example, the competitive advantage gained from implementing AI could lessen as market competition intensifies (Forum, 2025).

Annual private investment in artificial intelligence

Includes companies that received more than \$1.5 million in investment. This data is expressed in US dollars, adjusted for inflation.



Data source: Quid via AI Index Report (2025); U.S. Bureau of Labor Statistics (2025) OurWorldInData.org/artificial-intelligence | CC BY
Note: Data is expressed in constant 2021 US\$. Inflation adjustment is based on the US Consumer Price Index (CPI).

(Our World In Data, 2025)

It's crucial to enhance individuals' capability and enthusiasm to leverage AI by fostering a culture of inquiry, promoting experimentation, incentivizing innovation, showcasing how AI can enhance job satisfaction and fulfillment by becoming a friendly user tool, and exemplifying proper behaviors at the leadership level, thus accelerating certain processes of understanding and developing tasks. Organizations, policymakers, educators, and employees collectively bear the responsibility of cultivating the skills needed to thrive in the AI landscape. Our research indicates that these initiatives could yield substantial benefits, as employees proficient in AI are increasingly sought after and valuable.

Approximately 28% of respondents indicated that while they do not presently use AI at work, they believe they will in the future. This implies that the adoption of AI in professional settings is expected to rise and that the broader economic effects of AI are likely to grow in the future (Morikawa, 2025).

Companies operating in the information and communications sector, especially larger ones and those with a greater proportion of highly educated staff (including college and graduate degree holders), are more likely to adopt AI. Similarly, businesses that leverage big data display a comparable trend to those using AI, although a significant number of retail companies utilize big data, likely because they have access to and make use of point of sales (POS) information. In contrast, the profiles of companies that implement robots differ notably. As anticipated, manufacturing companies are the most common adopters, and the impact of firm size is considerably more pronounced compared to AI and big data usage (Morikawa Masayuki, 2024).

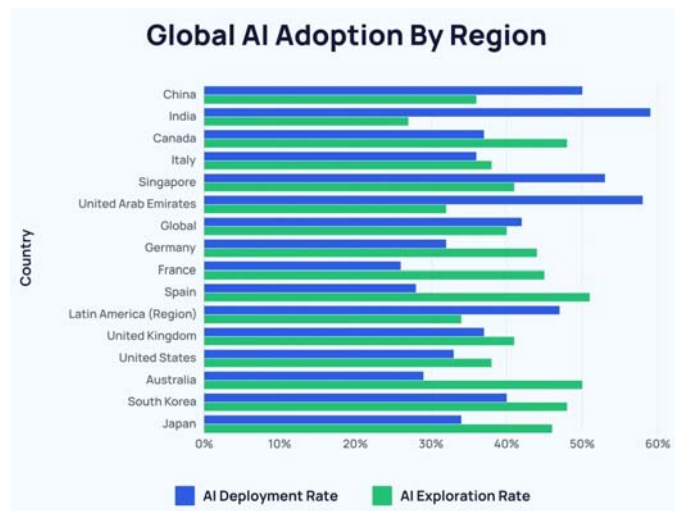
Moving Ahead with AI

One challenge presented by AI is the risk of technological exclusion, especially for workers with limited digital skills or those from older demographics. This could deepen inequalities

in the labor market by driving up the need for highly skilled individuals while sidelining others. Concerns about widespread job losses resulting from AI and its effect on employment are among the most frequently debated issues regarding technological advancements. However, when implemented carefully, AI has the potential to boost efficiency and create additional value (Grant, 2025).

An assessment of organizational needs and opportunities, along with investments in employee training, will be vital for defining the future of work in the AI-driven landscape. Clear communication is key to navigating change. Employees must grasp that technological innovations are intended to optimize processes, enhance productivity, and improve the quality of work instead of eliminating positions. Organizations should proactively address concerns by clarifying the motivations and objectives behind changes before they are enacted.

Organizations should tap into current employee capabilities and offer access to educational programs, guidelines, and pertinent courses. This enables employees to adjust to new technological settings while boosting their confidence in their roles. Instead of viewing AI as a threat, it should be regarded as an opportunity to promote innovation, enhance efficiency, and improve competitiveness in the digital era (Ozge Demirci, 2024).



(Anthony Cardillo, 2025)

Conclusion: Preparing for the Future of Labor with AI

Although AI introduces challenges like job loss from automation, it also brings many possibilities for job transformation and new roles. Succeeding in a future influenced by AI relies on accepting these technologies and preparing the workforce with the skills needed to adapt and succeed in changing job positions. By cultivating a culture centered on ongoing learning and innovation, society can fully leverage AI's potential, ensuring both economic advancement and enhanced quality of life for generations to come. The effect of AI on labor force is a complex and varied topic that will only increase in its possibilities to

develop. While AI may eliminate some jobs, it also has the capacity to generate new job opportunities, boost productivity, and spur innovation. To successfully navigate the challenges and possibilities of an economy shaped by AI, workers must prioritize reskilling and lifelong learning.

Businesses and governments need to collaborate to establish policies and initiatives that support workers during this transition and guarantee equitable distribution of AI's advantages. In the end, the work landscape with AI will emphasize collaboration rather than substitution. Employees who view AI as a means to improve their capabilities will be better prepared to succeed in a scenario where humans and machines join forces to tackle intricate challenges and promote advancement. To establish more effective and adaptable workforce development systems, we need to produce “headlight” data and analysis that utilize AI's ability to predict the impact of technology on skill requirements. AI and other modern technologies offer significant chances to develop new industries, boost productivity, and improve living standards. The decisions we make now to aid worker transitions — by enhancing data and transition assistance — will shape how the advantages of the future economy are distributed. Fostering a culture of ongoing learning is essential in today's AI-driven landscape. AI technologies can significantly contribute to this by suggesting individualized training programs, recognizing areas where skills are lacking, and proposing focused learning opportunities. In addition, immediate AI assistance can support employees as they navigate challenges, while predictive analytics can enable organizations to foresee upcoming training requirements.

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Artificial Intelligence in e-commerce-statistics and future trends

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Abstract. *This study analyzes the main evolutionary trends of e-commerce, mainly determined by artificial technology and digitalization. The introductory part presents this implementation way of artificial intelligence in e-commerce and its main future evolution trends. In the first part, the expansion of the use of chatbots and intelligent virtual assistants using NLP techniques is analyzed using statistical data, and in the second part, the influence of personalized marketing and the expansion of e-commerce platforms. The third part analyzes the mobile commerce (m-commerce), the main trend in the development of e-commerce. Finally, brief conclusions are presented, which of course also take into account the ethical side of future e-commerce trends.*

Keywords: electronic commerce, chatbot, virtual assistant/NLP, Q-commerce, m-commerce.

JEL Classification: O50.

Introduction

Electronic commerce refers to sales-purchase activities through remote data transmission, activities specific to the expansive marketing policy of commercial companies. It allows the participation of both natural and legal persons, as well as the state or its institutions. In an increasingly digitalized world, e-commerce brings numerous benefits to both consumers and businesses. Mainly, these are non-stop accessibility, global coverage, reduced costs and personalization and targeting (Ghibutiu A. 2003).

There are several categories of e-commerce dependent on the relationship between the participants: B2B (business-to-business) is an e-commerce model in which all participants are companies or other organizations, B2C (business-to-consumer) e-commerce model in which companies sell to individual buyers–natural persons, C2B (consumer-to-businesses) this e-commerce model refers to individuals (consumers) using the Internet to sell their products or services to businesses and to search for sellers to bid on products or services, C2C (consumer- to-consumer) this model refers to consumers selling directly to other consumers; E-government which exists in various forms, including B2G (business to government), G2B (government to business), and G2C (government to consumer).

The implementation of artificial intelligence by digital platforms involves the use of generative algorithms and machine learning, which has the consequences of optimizing customer relationships (using chatbots, intelligent virtual assistants with NLP techniques, personalized marketing by analyzing customer behavior and browsing history (cookies, reviews, forums) but also streamlining transactions by optimizing prices and securing the payment system.

If in the initial stage, transactions were only made on the desktop, now, with the widespread of the Internet among the population and the revolution of the Android system and IOT, they are made both on the desktop and on other devices, smartphones, tablets, etc. A major trend in the evolution of online commerce is mobile transactions, m-commerce, which will expand in the coming period.

1. Customer relationship optimization – chatbots and intelligent virtual assistants (NLP techniques)

Recent specialized studies and e-commerce events show that the dominant trend within commercial sites is the use of chatbots and intelligent virtual assistants that use NLP language techniques. Research shows that chatbots are increasingly implemented in messaging services and are considered an integral part of future consumer services. As such, 80% of businesses use or are in the process of implementing chatbots to communicate with users 24/7 and solve customer problems. (Nechifor E., Trifan A. 2021). According to a recent study by Market Research Center (a global market research company), the conversational artificial intelligence (AI) market is estimated to grow from 12.75 billion USD in 2024 to 36.54 billion USD by 2032, exhibiting a compound annual growth rate CAGR of 22.30% during the forecast period (2024-2032) for both types of conversational artificial intelligence (intelligent virtual assistants and chatbots). While the European

conversational artificial intelligence (AI) market currently accounts for the second largest market share, due to the increasing demand for reducing enterprises workloads related to customer engagement and retention, which is motivating the adoption of conversational AI solutions in Europe, the Asia-Pacific conversational artificial intelligence (AI) market is expected to grow at the fastest CAGR from 2023 to 2033.

This is due to businesses increasing knowledge of new customer support services and technologies. (Market Research Centre 2025). Marketing specialist Adam Connell concludes that the benefits of using chatbots are as follows: chatbots can answer up to 79% of routine questions, businesses save approximately 30% of customer support costs, and they can reduce response time to routine questions by up to 80%, and 31% of companies that personalized their chatbot messages achieved their goals. Regarding chatbot usage statistics, the following aspects are interesting: approximately 67% of global consumers have used a chatbot in the last year, customers use chatbots between 8 am and 5 pm, approximately 80% of users use chatbots when offered, chatbots manage conversations from start to finish approximately 70% of the time, etc. (Connell A. 2025)

AI assistants are software programs that use technologies such as natural language processing (NLP) to understand and respond to voice and text commands. They can perform tasks similar to human assistants, such as reading text, dictating, and making calls. Typically cloud-based, they offer accessibility from anywhere with an internet connection and can be integrated with smart devices for enhanced usability (McFarland, 2022).

The most advanced AI assistants use self-learning algorithms to provide highly personalized experiences, adapting to users preferences and speech patterns. A recent study conducted by CultIO (a Romanian market research company) on a sample of over 40,000 respondents, consisting of people aged between 18 and 55, from urban areas, with Internet access, establishes that almost all respondents (98%) claim to be familiar with the term "artificial intelligence", and of these, most assimilate this term with robots, ChatGPT, technology and computer and GPT chat is used by half of the respondents, most of whom are women, aged 26 to 39. Those who use this program the least are mostly women, from the age group 40 - 55 years old. (2023 Biz Magazine).

2. Personalized marketing and the extent of online e-commerce platforms

A second development trend in e-commerce under the influence of artificial intelligence is the personalization of marketing by adapting it to customer needs. Specifically, cookies and intelligent algorithms track consumers online browsing behavior, which allows e-commerce platforms to adapt their offers and even prices to market developments.

A responsive website changes (responds) to the user's needs and the device it is accessed from. According to Aly Media (digital marketing agency), the main characteristics of a responsive website are: it has dynamic content that changes, optimized images and correct spacing, it can work on mobile operating systems and the navigation is condensed. (ALY Media 2025). While online shopping has become a major part of the consumer shopping experience, offline shopping, i.e. buying in physical stores, is the most common way

products are purchased across many industries. Online shopping is most popular and most frequently performed among younger generations in modern countries around the world, with digital shoppers becoming increasingly ubiquitous, regardless of age or origin (Statista, 2025).

The following table, based on more recent statistics (2023), shows that the share of customers who prefer to shop online exceeds that of those who prefer to shop in physical stores, in the main developed economies, the exceptions being Australia and New Zealand:

Country	US	United Kingdom	Spain	Australia	New Zealand
On-line purchase preference 2023	43%	43%	32%	32%	25%
Store acquisition preference 2023	27%	27%	30%	35%	39%

Source: data processed from Statista 2025.

An important aspect of this trend is represented by the segment of the population that wants selected innovations in e-commerce worldwide, with an increasingly significant share of the younger generation (generation Z) in this category, as shown in the following table:

	Voice Assistance	Personalized Service	Personalized product recommendation	VR/AR
Gen Z 18-26 years	19%	37%	45%	29%
Millennials 27-42 years	23%	40%	45%	32%
Gen X 32-58 years	12%	31%	40%	35%
Old 59-77 years	10%	24%	32%	20%

Source: data processed from Statista 2025.

Along with personalized marketing, there is also an expansion of the use of traditional online commerce platforms in a globalized and digitalized world. Thus, in 2023, the Temu shopping app was the most downloaded e-commerce app in the United States on both IOS and Android devices, with 122 million downloads that year, followed by the fast fashion retailer SHEIN app with almost 21 million downloads on the Apple App Store and over 15 million on the Google Play Store.

According to a survey conducted in September 2023, by Statista, a total of 24% of online shoppers surveyed 42,510 people from 41 countries made their most recent cross-border purchase through Amazon, Alibaba/AliExpress 16%, Shein 9%, Temu and Ebay 7% each, other platforms 37%.

At the same time, it is noted that well-known social networks are quickly becoming a dominant force in e-commerce. Networks such as Facebook, Instagram and TikTok are very smart in connecting sellers with their target audience. With the emergence of marketplaces on social networks, they are now becoming direct competitors of B2C e-retailers. According to Statista, global social media revenues will experience an upward growth in the coming period from 821 billion USD in 2025, to 908.5 billion in 2026, to

997.3 in 2027, and to reach 1087 billion USD in 2028 (Fedorko R., Krail S. Bacik R., 2022). In this regard, marketing specialist April Lopez, in a study published on Medium, expands on the concept of Jay Abraham, founder and CEO of Abraham Group, according to which an activity develops with three basic principles, namely obtaining more customers, increasing the value of the order and its frequency, considering that obtaining a new customer costs 5 times more than keeping an old one. Additionally, a 10% increase in each category (10% more customers, 10% higher order value and 10% more frequent orders) results in a business growth of 33%, not just 30%. (Lopez A. 2025).

3. IOS and mobile-commerce – the future trend of online commerce

The widespread spread of IOT and the Android system determines the performance of online transactions from other devices, especially mobile. However, the average value of the online shopping order via smartphones and tablets still lags behind traditional e-commerce via desktop computers.

Regarding this aspect, it should be mentioned that online purchases via smartphones have an increasingly important share in Asia. In 2021, Malaysia was the largest digital market according to the percentage of the population who had bought something via phone, with almost 45% making a weekly purchase on mobile, starting with the first quarter of 2023, South Korea had the highest share of internet users who bought something online every week, with 44.4%, the global average being 29.9% of buyers.

Despite the fact that mobile devices offer a convenient and more accessible way to shop, computers and desktops remain the preferred choice for more expensive purchases. The online shopping cart abandonment rate has remained constant in the post-pandemic period, after reaching a historical high of 71.98% in 2013, as shown in the data processed in the following table:

Year	2013-reference	2020	2021	2022	2023	2024
shopping cart abandon rate	71,16%	69,8%	69,82%	69,99%	70,19%	70,19%

Source: data processed from Statista 2025.

The amplification of m-commerce is also analyzed by the 2 Performant platform, which is a tool that connects people skilled in online marketing with people in ecommerce who want to increase their sales.

Thus, compared to desktop transactions, mobile transactions are higher in percentage in each e-commerce store every day of the week, as shown by the data processed in the following table:

Day	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sameday
Dektop-%	3,27	3,25	3,15	2,89	2,81	1,48	1,73
Mobile-%	12,16	11,9	12,28	11,28	11,21	10,61	11,94

When do sales take place in an e-commerce store? (% transactions) - data processed from 2 Performant

As an average order value, however, desktop purchases are superior to mobile purchases every day of the week, as shown in the following table:

Average order value EUR	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sameday
Dektop	79.41	75.77	82.93	78.65	83.83	77.56	79.31
Mobile	54.62	51.98	51.94	51.95	51.33	50.64	51.11

How much does a customer spend in an e-commerce store? (average order value EUR) - data processed from 2 Performant

It turns out that the value of orders is higher in the first days of the week, the overall average being 57.39 EUR, of which 79.77 EUR from desktop and 52.22 EUR from mobile. Statistics and future forecasts show that the value of mobile transactions as well as the share of total global e-commerce retail are set to increase by 2028, as presented in the following table.

Year	2024	2025	2026	2027	2028
M-commerce revenue trillion USD	2,07	2,51	2,74	3,02	3,35
Share of total retail commerce	57%	59%	60%	62%	63%

Source: data processed from Statista 2025.

The implementation of artificial intelligence in e-commerce has positive consequences for its development in the coming period.

The following table presents, by comparison, the compound annual growth rate (CAGR) of retail e-commerce sales from 2024 to 2029, based on data provided by Statista in June 2024:

Country	India	China	US	Turkey	Brazil	Global
E-commerce Compound Annual Growth Rate (CAGR) 2024-2029	11,45%	9,95%	8,99%	11,48%	11,56%	9,4%

Source: data processed from Statista 2025.

In this regard, a growth rate above the global average of 9.4% is observed in the Asian countries of China 9.95% and India 11.45%, while the USA is below average, with a rate of 8.99%, the first places being occupied by Turkey with a rate of 11.48% and Brazil 11.56%. At global level E-commerce share of total global retail sales a fost de 20,1% iar retail e-commerce revenue worldwide de 4,12 trillion USD.

There is also an increase in global fast-paced commerce (Q-commerce), with the global value of revenues in 2024 estimated at USD 173.2 trillion, led by China with USD 47.7 trillion, followed by the USA with USD 21.9 trillion and Europe with USD 7.5 trillion.

An important aspect of the future of e-commerce is represented by the ethics of commercial transactions. A relatively recent study presents the main problems of e-commerce that Europeans have faced, namely: guarantees offered to consumers -56%, returns of goods

and price reductions -46%, delivery of goods, receipt of defective or wrong goods -25% or "extraction" of an amount greater than the one they agreed to -8% (Maruntelu I.2008). Specialists in the field require as mandatory features of a responsive website detailed information about the supplier and/or distributor, the privacy policy of customer data, taking into account the use of cookies, but also the product return policy. (Onete B.2008).

5. Conclusions

Trade, as an economic activity, existed long before the development of the market economy system. Developed in the last decades, electronic commerce represents the modern way of carrying out commercial exchanges. It has multiple advantages for companies, for consumers and for the whole society. Artificial intelligence, specific to the current period, is changing the traditional way of conducting e-commerce. If, in 2023, only 15% of companies in the field of commerce were using AI tools. today, the figure exceeds 70% in certain countries and can be a competitive advantage for domestic and cross-border trade. The major changes in e-commerce brought by AI are the optimization of customer relationships through the use of chatbots and intelligent virtual assistants with NLC technology that allow for efficient interaction with the customer, which determines the personalization of marketing according to the needs, demand and online behavior of buyers, along with the expansion of e-commerce platforms, along with the development of commercial activities through social networks, but also the scale of m-commerce. The recent conclusions of the Commerce Innovation Summit, organized by Netopia Payments and IC Events show that in the future, companies that use artificial intelligence in online commerce will have a 10-12% increase in revenue, according to market data, and the technology will increase profitability by 59% by 2035. An important aspect determined by these changes is represented by online payments and transaction security. Additionally, in the analysis of the future of e-commerce, its ethical component must also be considered.

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The evolution of the labor market in the context of economic crises and digitalization

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Abstract. *In recent decades, the labour market has been significantly influenced by global economic crises and technological advances, in particular digitalization. Economic crises, such as recessions and pandemics, have had a profound impact on unemployment rates, job structure and working conditions, sometimes leading to massive job cuts or changing skill requirements. At the same time, digitization has transformed the way work is done, through automation, remote working, online platforms and new business models. These developments have led to increased demands for digital skills and the emergence of innovative jobs, but also to the disappearance of some traditional jobs. As a research method we applied a multiple linear regression model to determine possible correlations between employment (dependent variable) and unemployment rate, inflation rate and economic growth rate (independent variables). After processing the historical data in the period 2006-2024 with the help of SPSS program, it turned out that the model is valid and there are semi-significant correlations between the dependent and independent variables. Major economic crises have significantly influenced the labor market, generating instability and uncertainty, thus both employees and employers have had to adapt quickly to new conditions.*

Keywords: labor market, unemployment, inflation, economic crisis, pandemic crisis.

JEL Classification: J21, J23, J24, O33.

Introduction

Labour market developments in the context of economic crises and digitization is a topical issue of great importance in understanding how societies and economies are adapting to the rapidly changing contemporary world. Economic downturns, such as global recessions or the COVID-19 pandemic, have had a profound impact on employment structures, leading to the decline of traditional jobs and the creation of new ones, often in innovative fields. In parallel, digitalization, accelerated by these crises, has transformed the way we work, creating both new opportunities and new challenges for employees and employers. This calls for a reassessment of training strategies, social protection and forced adaptation to new technological and economic realities. These labor market dynamics reflect not only changes in the structure of economies, but also in employment relations in an era where technology and economic uncertainty are merging into a changing landscape.

The paper has been structured in four parts:

Part I. We presented the particularities of the Romanian labor market in the period 2006-2024, and we chose this period because we wanted to see the impact of the two crises (the financial crisis of 2008 and the pandemic crisis of 2020), which were manifested in this period, not only in Romania but also worldwide.

Part II. We have presented the manifestations and causes of the 2008 financial crisis, as well as their effects on the most important macroeconomic indicators and especially on the labor market.

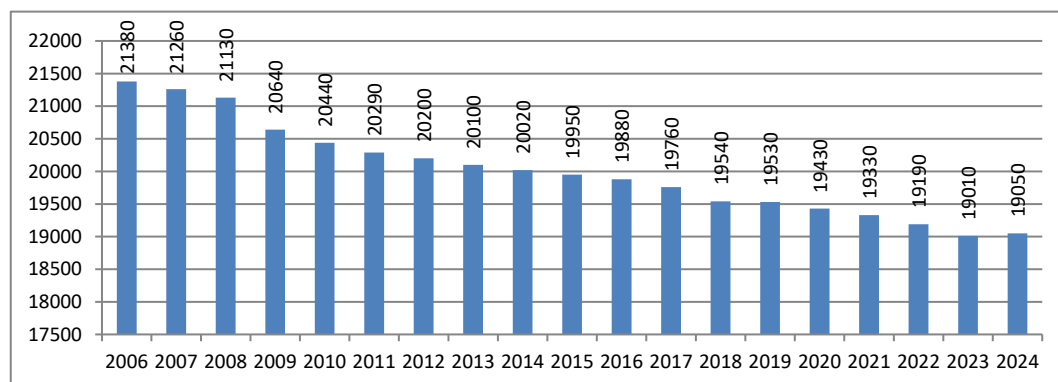
Part III. We presented the effects of the COVID-19 pandemic crisis on economic indicators and the labor market, as well as the main changes due to economic inactivity.

Part IV. The impact of digitalization and AI on economic activity processes. For this purpose we conducted a quantitative questionnaire-based research to capture users' perceptions of labor productivity and labor efficiency.

Part I. Particularities of the labor market during 2006-2024

During 2006-2024, the resident population gradually decreased from 21.38 million people to 19.05 million people, which indicates a demographic decline due to the decrease in birth rate and international labor migration, which also caused the decrease in the working population (see Table 1).

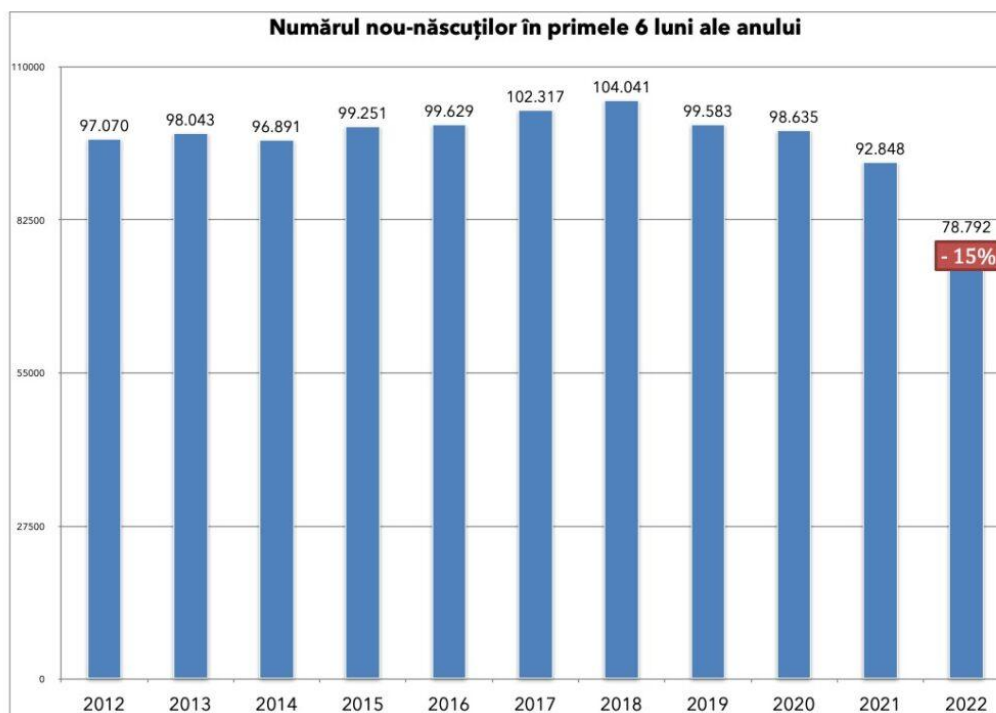
Table 1. Resident population on January 1, 2006-2024



Source: data provided by NSI, press conference 2006-2024, <<https://insse.ro/cms/ro/tags/comunicat-ocuparea-si-somajul>>

In Table 2. we can observe a decrease in the birth rate, thus the lowest number of births was registered in 2022, with 23 thousand children less than in 2021.

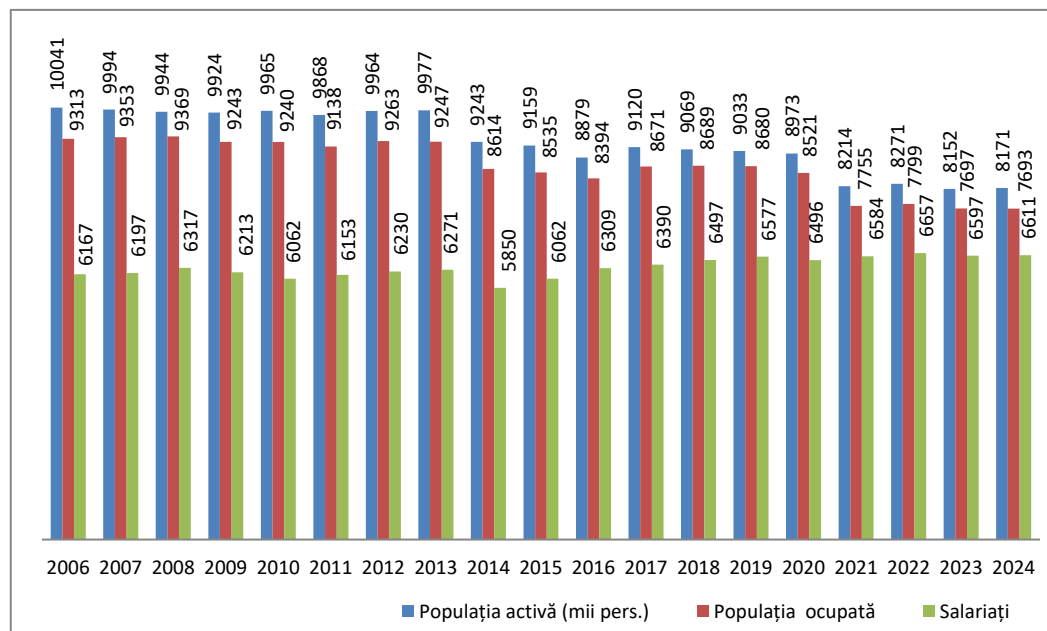
Table 2. Number of newborns in the first 6 months of the year, 2012-2022



Source: INS/Grafic edupedu.ro

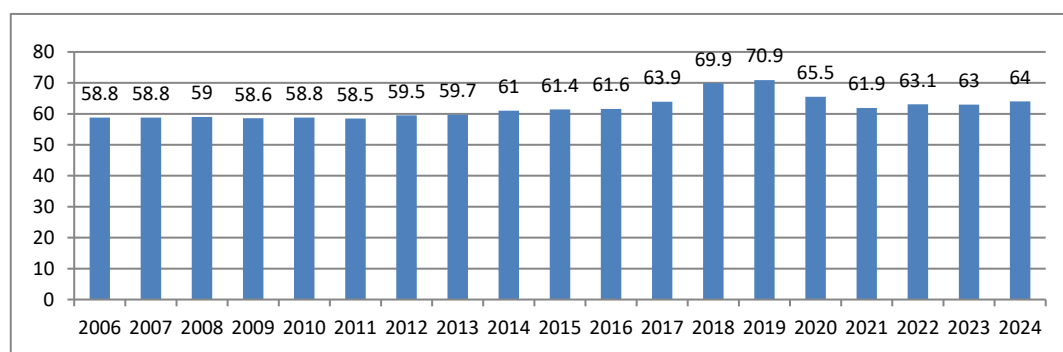
Amid the decline in total population, the available labor force decreased from 10,041 thousand persons to 8,171 thousand persons, a decrease of about 19% in 2024 from 2006.

The employed population decreased overall from 9,313 thousand persons in 2006 to 7,693 thousand persons in 2024. This suggests a downward trend in employed jobs or a possible withdrawal of part of the labor force from work. The number of employed persons, although fluctuating slightly, with a low in 2014 of 5,850 thousand persons, increased from 6,167 thousand persons in 2006 to 6,657 thousand persons in 2024 (see Chart 1). This suggests that there is a trend to employ more workers in a smaller labor market.

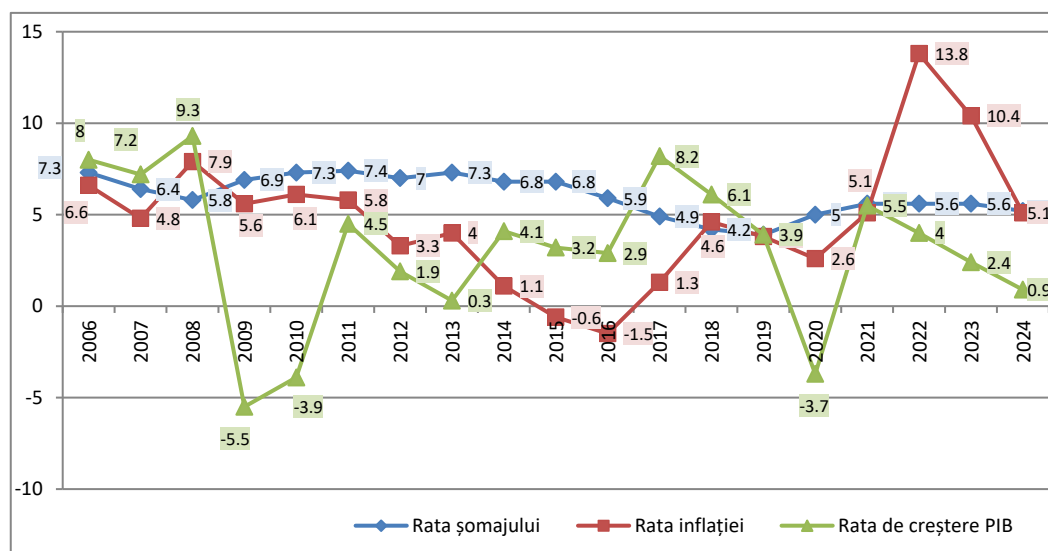
Graph 1. Evolution of the active and employed population between 2006-2024

Source: data provided by NSI, press conference 2006-2024, <<https://insse.ro/cms/ro/tags/comunicat-ocuparea-si-somajul>>

Analyzing the labor market indicators, we can see that during the period under analysis, the employment rate increased, reaching 70.9% in 2019, getting closer to the target of the Europe 2020 Strategy, launched by the European Union, with the main objective of smart, sustainable and inclusive growth (see Chart 2). One of the targets of the strategy was to increase employment, with the aim of reaching an employment rate of 75% for 20–64-year-olds by 2020. This target referred to promoting employment in the labor market, including by increasing access to education, training and improving working conditions across the European Union.

Graph 2. Employment trends in Romania, 2006-2024

Source: data provided by NSI, press conference 2006-2024, <<https://insse.ro/cms/ro/tags/comunicat-ocuparea-si-somajul>>

Graph 3. Development of GDP, unemployment and inflation rates between 2006-2024

Source: data provided by NSI, press conference 2006-2024, <<https://insse.ro/cms/ro/tags/comunicat-ocuparea-si-somajul>>

Chart 3 shows the evolution of the most important macroeconomic indicators in Romania during the period 2006-2024, a period in which two major crises occurred, the financial crisis of 2008 and the health crisis that started in early 2020. As we can see, the two crises have visibly produced changes at the macroeconomic level through decreases in macroeconomic indicators, namely real GDP per capita and through an increase in unemployment and inflation rates.

Part II. How did the 2008 financial crisis manifest itself?

First, we want to explain what an economic crisis is and to show what are the causes as well as the effects on the economy.

An economic crisis is a period of significant decline in economic activity in an economy or a wider region, manifested by several problems such as falling GDP, rising unemployment, firm failures, high inflation or deflation, declining confidence in the financial system and economic volatility. In this paper we will refer strictly to two crises that manifested themselves during the period 2006-2024 namely:

- **Global financial crisis of 2007-2008:** It was caused by the collapse of the US real estate market and the financial risks taken by big banks, leading to a global banking crisis and a severe economic recession.
- **Economic Crisis of 2020 (COVID-19):** The global pandemic of COVID-19 has led to the closure of economies in many countries, a fall in demand and production, and a rise in unemployment. This was one of the most rapid and major economic crises in history.

Economic crises are often caused by internal and external factors, and their effective management requires appropriate economic policies, international coordination and, in many cases, long-term structural reforms.

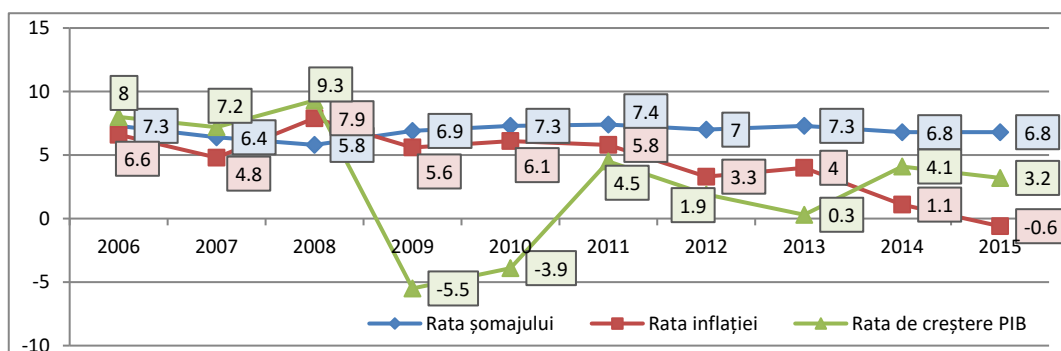
The crisis was caused by a number of interconnected factors, but the main causes were:

- **The collapse of the US housing market:** In the run-up to the crisis, banks in the United States made risky loans for home purchases, particularly subprime loans (loans to people with low credit scores). These loans were often packaged in complex financial instruments known as Mortgage-Backed Securities (MBS).
- **The collapse of large financial institutions:** Banks and other financial institutions over-invested in these securities, which rapidly lost value as real estate values fell. Banks and financial institutions became vulnerable to bankruptcy, and some of them, such as Lehman Brothers, Bear Stearns and Merrill Lynch, went bankrupt in September 2008.
- **Risky financial speculation:** Many investors speculated in the real estate market, but also in other financial markets. These speculations created an economic bubble that collapsed abruptly when real estate prices started to fall. Lack of financial regulation: Prior to the crisis, financial regulation was rather weak. Many banks and financial institutions took huge risks without effective regulatory oversight.

The impact of the 2008 financial crisis on the main macroeconomic indicators (real GDP per capita, unemployment rate and inflation rate)

- **Rising unemployment rate:** In Romania, the unemployment rate rose significantly **between 2008 and 2010, from 5.8% in 2008 to 7.3% in 2009 and 7.4% in 2010**. This increase has been linked to falling demand for products and services, which has led to downsizing and business closures (see Graph 4).
- Before the outbreak of the financial crisis, Romania's economy had a **GDP growth rate of 9.3% in 2008**, after the crisis, it fell by **5.5% in 2009 and 3.9% in 2010**, which led to a reduction in domestic and foreign demand, a fall in exports and difficulties in obtaining financing from banks.
- In 2008, **inflation** was high at 7.9%, because it reflected the price pressure before the crisis, then in 2009 it fell to 5.6% as a feature of the economic recession, consumers cut spending and prices stabilized, in 2010 the inflation rate rose to 6.1% due to the increase in fuel and agri-food prices, but in 2011-2015, inflation fell, reaching 3.3% in 2012 and in 2015 it recorded negative values (-0.6%).

Graph 4. *Unemployment, inflation and GDP growth rates*



Source: data provided by NSI, press conference 2006-2015, <<https://insse.ro/cms/ro/tags/comunicat-ocuparea-si-somajul>>

The 2008 financial crisis caused a number of changes in the labor market:

- **Changes in employment structure:** A significant proportion of people migrated to the informal sector, where even without access to legal labor protection, wages were lower but less exposed to the economic pressures of the formal sector. This increased the number of people employed in the **gray economy or in temporary work**.
- **Increase in the number of part-time workers:** Another important change has been the increase in the number of people employed on **part-time or temporary contracts**.
- **Changing employment profile:** Another significant effect has been an increase in the number of **highly-skilled workers in certain sectors**, in response to the need to respond to changing economic demands and to become more competitive in the labor market.
- **Migration of workers:** The crisis has caused a significant change in forced migration of workers in Romania, with almost 2 million Romanians leaving the country, a phenomenon that has had a significant impact on the labor force.
- **The increase in the number of emigrants** in the construction and service sectors has led to a significant loss of labor in these sectors and has reduced the productive capacity of the Romanian economy.
- **Falling incomes and rising wage inequality**, as people in the most affected sectors suffered large income losses, while some less affected industries, such as IT or telecoms, continued to have higher wage levels.

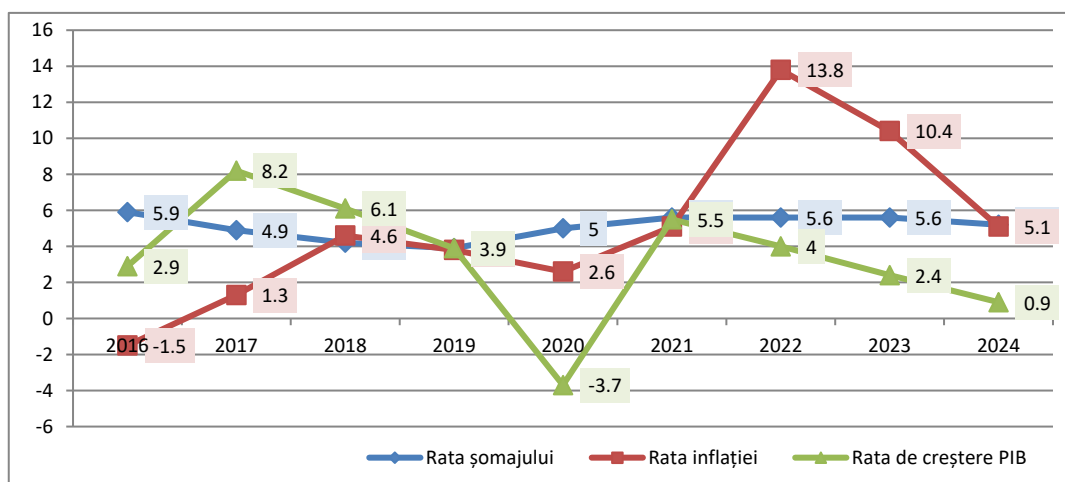
Part III. The COVID-19 pandemic crisis - causes and effects

The COVID-19 pandemic crisis had a **significant and lasting** impact on the Romanian labor market. From rising unemployment and job losses in vulnerable sectors to accelerating automation and digitization, the crisis has led to fundamental changes in the structure of the labor market. Government support measures, such as **technical unemployment and economic** incentives, have largely helped to limit the immediate negative impact, but the economic and social challenges posed by the pandemic will continue to have long-term effects.

In the period 2016-2019, the unemployment rate fell, reaching a low of 3.9% in 2019, then after the outbreak of the pandemic, the unemployment rate rose slightly to 5% in 2020 and then in 2021-2023 it remained constant at 5.6%, and in 2024 it slightly decreased (5.2%).

The inflation rate had significant fluctuations, in 2016 it was negative (-1.5%), which means deflation, and after that it started to increase, during the pandemic it recorded slight increases, but in 2022 it reached the highest value in recent years, namely 13.8%, and in 2023 it was 10.4%, in 2024 inflation moderated and at the end of the year it was 5.1%.

In 2017, Romania recorded **an economic growth of 8.2%**, but after this year the growth rate decreased, but remained positive until 2019 (3.9%), due to the pandemic, there was an economic decrease of -3.7%, from 2021 the economy started to recover, recording a growth of 5.5%, but in 2022 it decreased to 4% and in 2023 to 2.4%, and in 2024 there was a significant economic cooling due to inflation, higher production costs and economic and social uncertainty (see Chart 5.)

Graph 5. *Unemployment, inflation and economic growth rates, 2016-2024*

Source: data provided by NSI, press conference 2016-2024, <<https://insse.ro/cms/ro/tags/comunicat-ocuparea-si-somajul>>

The particularities of the pandemic crisis on the labor market

The pandemic led to an **increase in the unemployment rate**, and employees were forced into **technical unemployment** (an important temporary measure introduced by the Romanian government to support employers and employees, especially in sectors such as **HoReCa, tourism, transportation, and events**). This has helped to reduce the number of unemployed, but at the same time has affected the incomes of many workers. Job losses and layoffs particularly in vulnerable sectors: tourism and HoReCa (restaurants, hotels and travel agencies have suffered significant losses) and transportation, including airlines and public transport. **Forced migration of the labor force**, those who worked in other countries (Spain, Italy) had to return to Romania, leading to increased competition on the labor market and pressure on the social security system. **The widespread adoption of telework** (IT, education, professional services), which has brought **benefits** (flexibility and time-saving), but has also created challenges related to lack of **appropriate equipment, difficulties in managing teams and psychological challenges**.

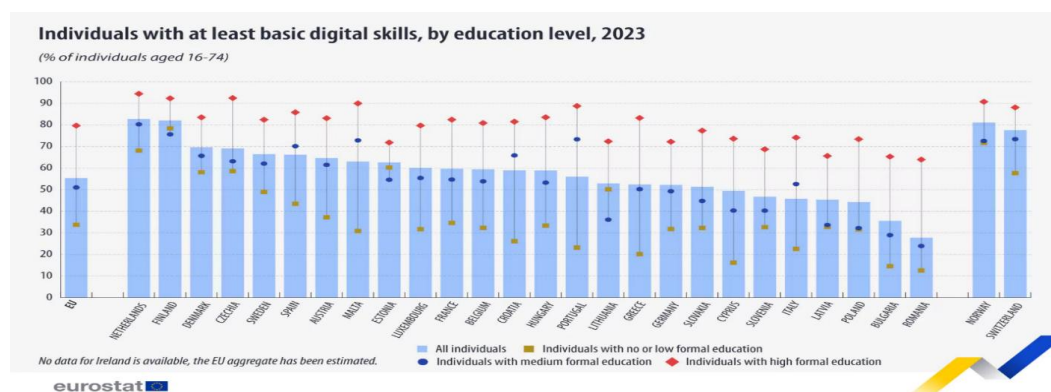
Economic developments in 2016-2024 reflect an economic cycle with rapid expansion in the early years (2017-2019), followed by a severe economic downturn in 2020 due to the pandemic, and a partial recovery in 2021, followed by an **economic cooling** in 2022-2024. **Projections for 2024** point to a slower economy with modest economic growth and still high inflation, suggesting that Romania may face difficulties in maintaining long-term sustainable economic growth without structural reforms or additional economic measures.

Part IV. The influence of digitalization on the labour market, opportunities and challenges

Automation of repetitive jobs (supermarkets have replaced cashiers with automated tills, in industry robots can assemble parts or sort products, etc.), so some will lose their jobs and have to move into more technical jobs, others will be in high demand (software developers, cyber security experts or designers). Demand for jobs in IT and technology is growing, many marketing firms are hiring people for SEO (search engine optimization) to improve the online visibility of their business. Telecommuting - offers flexibility and makes it possible for employers to hire people from anywhere in the world, which means more competition in the labor market. The existence of online platforms (Upwork or Fiverr), allow people to find short-term projects or freelance, but incomes can be unstable, and they may not be able to benefit from insurance or paid leave. Online recruitment, through platforms such as LinkedIn or job sites, so employers can reach candidates in different corners of the world faster. Higher paying jobs, but also precarious jobs, the key is continuing education and adaptability to stay competitive in the labor market.

Basic digital skills are an essential prerequisite for effective integration into the labor market in an economy undergoing a technological transformation. According to the 2023 data, the analysis of the distribution of these skills according to educational attainment reveals a direct correlation between educational attainment and overall literacy. People with tertiary education register the highest share of basic and advanced digital skills, while people with elementary or intermediate education have significantly lower levels. From an economic perspective, the digitally unskilled workforce is becoming vulnerable to automation and the accelerating digitization of the productive and administrative sectors (see graph 6).

Graph 6. Individuals with basic digital skills, by level of education, 2023

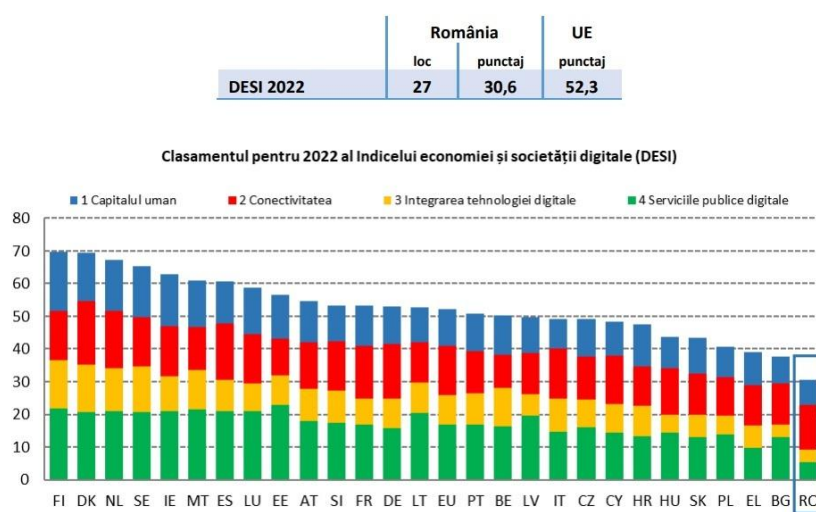


Source: <https://economy.media.ro/romania-pe-ultimul-loc-din-uniunea-europeana-in-clasamentul-competentelor-digitale-eurostat.html>

According to the 2022 edition of the Digital Economy and Society Index (DESI), Romania scored 30.6 points, down from 32.9 points in 2021, thus remaining at the bottom of the EU rankings (see Chart 7). In the 11 years of the European Commission's Digital Economy and Society Index, Romania has only ranked better in 2019 and 2020, when it was in second

last and second last place respectively. The European Commission warns that the low level of digitization negatively affects the country's economic potential, and the stagnation in the digitization of public services has a direct impact on both citizens and the business environment.

Graph 7. Economy and digitalization index in Romania VS European Union, 2022



Source: <https://search.app/sDCfkxeVH2Ag8p548>

Methodology of scientific research

To show that economic crises of any kind can influence labor market indicators, we conducted quantitative research based on an econometric simple linear regression model that analyzes the correlations between the employment rate as a dependent variable and three independent variables, namely the unemployment rate, the inflation rate and GDP growth rates, using historical data from 2006-2024, using SPSS.

The proposed econometric model is a multiple linear regression model of the form:

$$Go = \beta_0 + \beta_1 \cdot \text{Unemployment rate} + \beta_2 \cdot \text{Inflation rate} + \beta_3 \cdot \text{GDP growth rate} + \varepsilon$$

where: Go - employment rate; β_0 - free term; β_1 , β_2 , β_3 - coefficients of independent variables; ε - random error

Table 1. Model estimates

Variable	Coefficient (β)	p-value	Interpretation
Intercept (β_0)	62.4	0.001	Basic employment rate
Unemployment rate	-1.8	0.012	The baseline employment rate 1% increase in unemployment will lead to a 1.8% decrease in the employment rate
Inflation rate	-0.3	0.150	The relationship is negative but significant
GDP growth	+0.9	0.005	1% increase in GDP will lead to a 0.9% increase in the employment rate

Source: data from historical data processing over the period 2006-2024 using SPSS.

The coefficient of determination, $R^2 = 0.82$, which means that 82% of the variation in the employment rate is explained by the regression model, i.e. the independent variables (Unemployment rate, inflation rate and GDP growth), it has a value approaching 1, which means that the model explains all the variation, so it shows that the linear regression model fits the observed data. The **Durbin-Watson** statistical test detects the correlation between successive error values over time, so in our case this test is 2.1 and we can say that there is no significant autocorrelation in the residuals, in other words the regression model is ok, and the errors are not correlated with each other, so it is valid from this point of view. **P-value** of the model is 0.001 which tells us that the model is statistically significant. Thus, we can present the correlation matrix in Table 2.

Table 2. Correlation analysis

	Employment rate	Unemployment rate	Inflation rate	GDP growth
Employment rate	1.00	-0.85	-0.45	+0.78
Unemployment rate				
Inflation rate				
GDP growth				
Employment rate				
Unemployment rate	-0.85	1.00	+0.30	-0.65
Inflation	-0.45	+0.30	1.00	-0.40
GDP growth	+0.78	-0.65	-0.40	1.00

Source: data from historical data processing over the period 2006-2024 using SPSS.

Between the employment rate and the unemployment rate there is a strong correlation (-0.85), so when the unemployment rate increases the employment rate decreases, for example in 2019, the unemployment rate was 3.9% and the employment rate was almost 70.9%, in 2020, the unemployment rate increased to 5% and the employment rate reacted sensitively to this increase, so it decreased to 65.5%.

Between the employment rate and the inflation rate there is a moderately negative correlation (-0.45), thus the increase in inflation seems to be associated with a slight decrease in employment, except in 2022, where inflation was 13.8% and employment remained realistically stable (63%), this is due to public policies that supported employment during the pandemic period, but also due to the 4% increase in GDP.

There is a strong positive correlation (+0.78) between the employment rate and the GDP growth rate, which we can say that economic growth stimulates employment, for example in 2027, GDP grew by 8.2% and employment rose to 63.9%, and in 2020, when GDP fell by 3.7%, employment also fell to 65.5%.

Research conclusions

Unemployment rate and GDP growth are the main predictors of employment rate. In this model, inflation is not significant, but its negative relationship suggests that anti-inflationary policies could boost employment. Unemployment is inversely correlated with employment, confirming Okun's Law in economics. The crises of 2008 (financial crisis) and 2020 (COVID-19), appear as anomalies, because they show that external shocks disrupt standard econometric relationships. The model presented also has limitations, it analyzes quantitative factors and ignores qualitative factors such as government policies

and access to technology. The model has limited predictive power (18 years), and the employment rate may be influenced by lagged factors, given that negative shocks propagate much faster than positive shocks.

Conclusions

Economic crises, such as the global recessions or the 2008 financial crisis, have forced many companies to adopt digital technologies to cut costs and remain competitive. These changes have also been accelerated by the COVID-19 pandemic, which has led to a rapid migration of workplaces towards digitization (teleworking, e-business, automation). Both economic crises and digitalization have changed the structure of the labor market. Some jobs have disappeared while others have evolved significantly. For example, traditional jobs in retail or manufacturing have been replaced by positions in technology, digital marketing or online services. While economic crises have led to many job losses in traditional sectors, they have also created new opportunities in emerging sectors such as technology, digital health or e-commerce.

Digitization has allowed the labor market to diversify, with more flexible jobs and remote work opportunities. To cope with these changes, governments need to implement policies to support the retraining of those affected by the economic downturn and digitalization. Continuing education and training are becoming essential to help the workforce adapt to market demands. Adaptability and the development of digital skills are essential to meet these challenges, and governments and companies must invest in helping employees to navigate these economic and technological transitions.

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