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## Article

# The impact of artificial intelligence applied in businesses on economic growth, welfare, and social disparities

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## THE IMPACT OF ARTIFICIAL INTELLIGENCE APPLIED IN BUSINESSES ON ECONOMIC GROWTH, WELFARE, AND SOCIAL DISPARITIES

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### Abstract

Previous literature on the impact of the application of artificial intelligence in businesses on economic growth, welfare, and social disparities is scarce, due to limited data and the recent dynamics of the field. To contribute to this gap, the study employs the percentage of large enterprises in the European Union (EU-27) using artificial intelligence technologies in production for the year 2021. The results obtained by static analysis (Feasible Generalized Least Squares method) indicate positive relationships between the application of artificial intelligence in large enterprises in European Union countries and economic growth, while the analysis of welfare and social disparities leads to mixed results: increasing the average net income per person, respectively, the poverty threshold and decreasing the number of people at risk of poverty and unemployment. Spatial analysis (Spatial Lag Model) of the economic and social impact of artificial intelligence applied in a country's large enterprises on neighbouring countries leads to robust results for economic growth and net average income per person, whose levels are positively influenced, through spillover effects and spatial interactions between states. At the microeconomic level, the study highlights the need for rapid adaptation of enterprises to artificial intelligence, and from the perspective of public policies, the need for transparent and sustainable regulations.

**Keywords:** Artificial intelligence (AI); enterprises, growth; welfare; unemployment; European Union.

**JEL Classification:** O11, B55, O33, C58, O52

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## Introduction

On its way to becoming ubiquitous in the contemporary world (Liefvooghe and van Maanen, 2023), artificial intelligence (AI) profoundly influences the economy and society (Luan et al., 2020; Dinu, 2021). Businesses are tempted to adopt AI technologies at a rapid pace, as artificial intelligence is the major source of innovation (Pelau et al., 2021), contributes to performance and revenue growth and reduces costs for most enterprise functions (Ruiz-Real et al., 2020), leads to better governance and optimised decision-making processes (Ginguş et al., 2023), increased capacity for data collection and analysis, efficient management of malfunctions or crises, supervision, safety and increased productivity of employees, etc. (Sipola, Saunila and Ukko, 2023). It is estimated that by 2026 the compound annual growth rate of the global enterprise artificial intelligence technology market will be around 35% to \$53.06 billion, compared to \$4.68 billion in 2018 (Herrmann, 2022).

Delineating the scope, valences and economic and social impact of artificial intelligence used in enterprises is challenging and a critical topic, exposed to major information and societal risks, as well as ethical aspects (Tăchiciu, 2019; Meghişan-Toma et al., 2022; Fulop et al., 2023).

The influence of artificial intelligence on the economy and society is still largely unknown, but early studies suggest that all social systems, including economics, politics, science, and education, are impacted by artificial intelligence technologies (Luan et al., 2020). Concerns are emerging in the public, academic, and political domains regarding the impact of the application of artificial intelligence in enterprises on the well-being of employees, jobs and, implicitly, of people at risk of poverty and social exclusion (Acemoglu and Restrepo, 2019; Lu, 2022). Studies analysing the influence of artificial intelligence on jobs and income distribution reveal heteroclite results, generate polemics, and open chapters of unforeseen social and economic changes, whose impact and effects are difficult to estimate at present.

In the context of technology-driven economic development theories, the study aims to answer the following research questions:

1. To what extent is economic growth in the member states of the European Union (EU-27) influenced by the application of artificial intelligence technologies in businesses?
2. Does the deployment of artificial intelligence technologies in enterprises in the European Union (EU-27) impact welfare and social disparities in income and unemployment?
3. Does the implementation of artificial intelligence technologies in companies in the European Union (EU-27) in one country influence economic growth, welfare, and social disparities in neighbouring countries?

The central objective of the study is to analyse the impact of artificial intelligence in businesses on economic growth, respectively, welfare, and social disparities in terms of income (people at risk of poverty or social exclusion, poverty threshold) and unemployment, by developing empirical research at the European Union (EU) level by 2021.

This paper addresses a topic rarely explored and not adequately clarified in the previous literature, contributing to it in several ways. First, it empirically studies, based on static and spatial analysis, the situation of a conglomerate of countries represented by the EU member states, at the intersection between artificial intelligence in enterprises and socioeconomic development. Second, the study is based on the theory of endogenous economic growth

theory (Romer, 1990), in which innovation, R&D and human capital are considered catalysts for economic growth. Third, the study addresses an identified literature gap on the social implications of adopting artificial intelligence technologies in enterprises. The research also presents managerial implications in terms of public policies, whose relevance in the current context is defining for the transparent, reliable, secure, and sustainable future configuration of artificial intelligence in enterprises.

The following sections of the paper are organised as follows: section 1 briefly presents the relevant literature, section 2 describes the data used and the research methodology, section 3 analyses the results obtained, section 4 contains the discussion, and the final section concludes on own contributions, limitations, and future research directions.

## **1. Literature review**

### **1.1. Implementing artificial intelligence in enterprises**

Artificial intelligence is used in enterprises to increase production and efficiency, in areas such as machine learning, learning, robotics, neural networks, and continuous learning, which with the help of ERP (Enterprise Resource Planning) applications uses artificial intelligence in financial management, production process, customer service, sales, analytics, forecasting (Kundurur, 2023). Artificial intelligence is used in enterprises in other areas and subfields: decision support systems, big data, cloud computing, graphics and tensor processing units, metaheuristics, etc. (Herrmann, 2022). The implementation of artificial intelligence in enterprises is most often associated with benefits for them, in terms of organisational efficiency, entrepreneurial culture, and decision-making processes (Ransbotham et al., 2021).

Although most studies highlight the benefits of using artificial intelligence for enterprises, there are also points of view that contradict this hypothesis, namely: at the initial stage of implementation, enterprises need to involve all relevant stakeholders, because the impact of artificial intelligence is far-reaching, then the value system is questioned, and thirdly, controlled experiments need to be done, as the equipment only imitates human thinking, which generates various risks (Holtel, 2016).

### **1.2. The link between artificial intelligence applied in enterprises and economic growth**

Studies on the influence of the implementation of artificial intelligence technologies in enterprises on economic growth are quite limited and are based, in the absence of quantitative data, mainly on theoretical reasoning, value judgments, or forecasts.

On the one hand, the application of artificial intelligence in enterprises contributes to improving product quality and productivity growth, work efficiency, increased customer satisfaction, having beneficial effects on the economy and ensuring long-term economic growth (Gonzales, 2023). Artificial intelligence is an important innovation in science and technology, can be considered a new factor of production, influences economic growth through three channels: automating complex physical tasks, supplementing the workforce, and promoting innovation in almost all industries (Yugang, 2019).

The most used information capturing the intensity of artificial intelligence application in enterprises refers to industrial robots, artificial intelligence patents, and artificial intelligence start-ups (Furman and Seamans, 2019). An analysis developed for 77 countries between 1993

and 2019 (Gong et al., 2023) shows that industrial robots can stimulate economic growth, but structural changes in the labour market and job losses are concerns that need to be focused on public policies.

On the other hand, skeptics of the field raise legitimate questions about the effects robots (as substitutes for labour-based production and conventional equipment) on economic development and launch ideas that demand for labour is likely to decline, threatening a decline in wages, savings, and economic well-being of current and future generations (Sachs, Benzell and LaGarda, 2015).

Based on the previous literature, the study's first research hypothesis assumes the following:

**H<sub>1</sub>:** The application of artificial intelligence in enterprises positively influences economic growth in the Member States of the European Union.

### **1.3. The impact of artificial intelligence in enterprises on welfare and social disparities**

The current wave of technological change based on advances in artificial intelligence has created widespread fear of further increases in inequality and job losses (Ernst, Merola and Samaan, 2019). While the incipient literature addresses emerging concepts such as the 'digital divide 1.0/2.0' generated by inequalities in digitalisation (Harambam, Aupers and Houtman, 2013), new artificial intelligence technologies are likely to lead to evolved forms of gaps, superior in nature and intensity, which could massively contribute to widening social differences in individuals' well-being.

Beyond the hyperbole and exaggerations of approaches specific to the application of artificial intelligence in companies, concerns about their effects on the well-being of individuals are a topic of current interest, addressed by previous literature, especially from the perspective of the labour market and unemployment (Mutascu, 2021).

The complex facets of welfare (or well-being) – social, material, financial, economic, personal, etc. – reflect relative, subjective, multidimensional, and difficult-to-scale notions that imply, in a broad sense, a high satisfaction of human existential and cultural needs (Polak, 2021a). The perception of well-being is directly related to a pejorative side of well-being, represented by the phenomenon of poverty and well-being related to working conditions and the environment (Wiśniewski, 2018).

Social income disparities affect contemporary economies, which are subject to profound social and economic challenges (Manta et al., 2023) and where new technologies and artificial intelligence are perceived as generating risks and possible scenarios, where there will be "winners and losers" (Goralski and Tan, 2020). Social inequalities in income are expected not only within a nation state, but also from a comparative international perspective, with artificial intelligence expected to contribute to poverty reduction in poor countries, while in developed countries it is expected to lead to significant job losses (Goralski and Tan, 2020). According to a study developed for the United States between 2011 and 2021, different types of technology influence the labour market inhomogeneously: industrial robots and software are associated with lower individual wages, while occupational exposure to AI technologies leads to higher individual wages (Fossen, Samaan and Sorgner, 2022).

The literature on the link between artificial intelligence and poverty is relatively new and contains a small number of studies (Mhlanga, 2021), mainly based on theoretical reasoning and without benefiting from empirical or econometric approaches, amid a reduced series of

data and the recent expansion of the field, still not explored in scientific research. New technologies have enabled unprecedented growth in labour incomes, but at the same time represent disruptive elements of the labour market, as technology has increased productivity, which in turn has led to strong GDP per capita growth, but labour gains can come in bursts and favour some sectors over others, leads to polarisation of earnings, favours highly skilled workers, and disadvantages those with low skills (Peralta-Alva and Roitman, 2018). Innovation has the potential to reduce poverty (Pansera and Martinez, 2017).

In contrast, studies on the influence of artificial intelligence on the labour market and unemployment are numerous and generally fall into two antagonistic currents, but many of them do not provide categorical results, but outline specific situations for certain industries (Georgieff and Hyee, 2021). An economic dystopia of extreme inequality and class conflict (Berg, Buffie and Zanna, 2018) was suggested a few years ago by some researchers, concerned about the expansion of robots in enterprises where workers would become serfs working on behalf of robot masters, in a new form of "economic feudalism" (Freeman, 2015) or workers would even lose their jobs (Oravec, 2019). There is a consistent literature addressing the risk of job automation and its impact on employment (Frey and Osborne, 2017; Haiss, Mahlberg and Michlits, 2021).

In the absence of reliable data on the application of artificial intelligence technologies in enterprises, many empirical studies in recent years have focused on capturing the phenomenon of artificial intelligence through indicators such as the number of industrial robots in enterprises or artificial intelligence patents, which have been analysed in interdependence with unemployment and associated phenomena, such as "replacement effect" or job creation ("displacement effect"), (Mutascu, 2021). Based on the analysis of the period 2012-2019 in 23 OECD countries and for 36 occupations, Georgieff and Hyee (2021) conclude that there is no clear relationship between exposure to artificial intelligence and employment in all occupations. Research developed for 74 countries and the period 2004-2016 (Fu et al., 2021) shows that industrial robot deployment has heterogeneous effects between developed and developing economies. In developed economies, robots improve labour productivity and total employment, whereas in developing economies there is no clear evidence of these effects. The impact of robots on income inequality also reveals mixed results. It appears that the increased adoption of robots is making the rich richer, although there is no evidence of the so-called technological unemployment (Fu et al., 2021).

Technological progress could lead to job losses in some sectors, but even when that happens, other sectors will expand and contribute to overall employment and wage growth (Acemoglu and Restrepo, 2019). The use of artificial intelligence has a favourable effect on the labour market, although the number of jobs in companies decreases, workers retrain to other professions, thus the unemployment rate is decreasing (Lu, 2022).

On the basis of the previous literature, the second hypothesis of the work is formulated:

**H<sub>2</sub>:** The application of artificial intelligence in companies negatively impacts the welfare of people and contributes to widening social disparities in the Member States of the European Union.

The expected meanings of the influence of the application of artificial intelligence in enterprises on welfare and social disparities in income and unemployment are: expectations of a decrease in average net income per person, an increase in the number of people at risk

of poverty or social exclusion, an increase in the poverty threshold, and an increase in the annual unemployment rate.

The European Union represents an area of analysis in which common policies aim to reduce economic and social inequalities between member states. Based on common policies of free movement of goods, capital, and labour, the third hypothesis of the study is configured:

**H<sub>3</sub>:** The application of artificial intelligence in businesses in one European Union country influences economic growth, welfare and social disparities in neighbouring countries.

Based on the results of the previous research presented, the research model is proposed (Figure no. 1), which captures the influence that the application of artificial intelligence in enterprises has on economic growth, welfare, and social disparities (in terms of income and unemployment), in the EU member countries (2021).

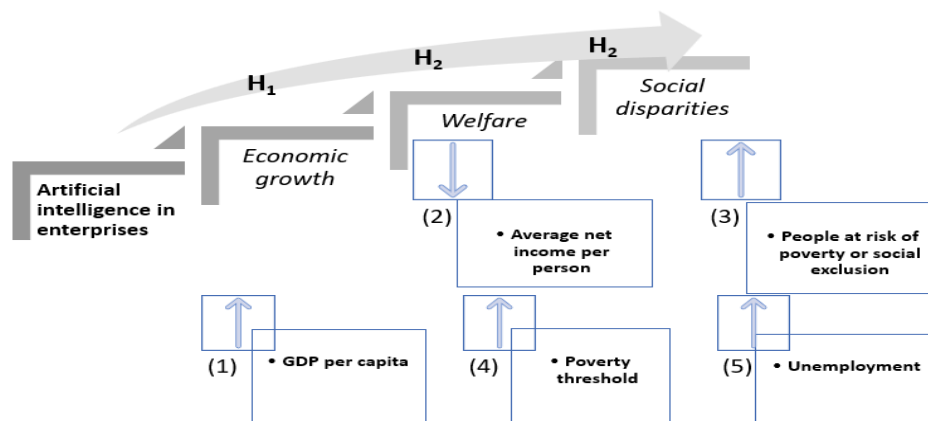


Figure no. 1. Theoretical model of research

Source: authors projection

## 2. Research methodology

The study develops multiple regression models for cross-sectional data for EU member states and the year 2021, with the aim of determining whether the deployment of artificial intelligence in enterprises impacts economic growth, welfare, and social disparities (represented by income inequalities, risks related to poverty levels, and unemployment).

The study develops multiple regression models (Feasible Generalized Least Squares, FGLS) and spatial analysis (Spatial Lag Model, SLM) for cross-sectional data for EU member states (EU-27) and 2021 for all variables included in the analysis. The aim is to determine whether the implementation of artificial intelligence in businesses impacts economic growth, welfare, and social disparities. The choice of the FGLS analysis method was based on its potential to manage aspects of heteroscedasticity and which, even under conditions of homoscedasticity of errors, leads to more efficient estimates than the least squares method, through the ability to manage various other forms of correlation between variables.

In the first phase of the research, the data were analysed from the perspective of classical regression assumptions, respectively, whether they are affected by multicollinearity,

heteroscedasticity, non-normal distribution, or non-stationarity of variables. Endogeneity is an aspect often ignored in economic studies that leads to inconsistent estimates. Endogeneity occurs either when two variables influence each other simultaneously, or when relationships between two or more variables are influenced by a factor that is not considered, or when dynamic endogeneity occurs, if the present values of a variable are influenced by its past values or those of other variables (Chatterjee and Nag, 2023). Based on these considerations, the applied strategy was to apply theoretical reasoning to identify the relationships between the variables, followed by the analysis of the Durbin-Wu-Hausman test to identify the endogeneity of the variables.

A spatial analysis was chosen for the efficient management of endogeneity (Petrovici et al., 2023), as it can capture spatial autocorrelation and control endogeneity problems that may arise due to spatially correlated errors or omitted variables. Spatial analysis can also manage cross-sectional dependence, given that data are susceptible to intra-state effects generated by common unobservable factors or common features. The study applies the Spatial Lag Model, which has the ability to effectively control data endogeneity, due to observations available for only one year and without the possibility of using dynamic analysis models. The Spatial Lag Model is used to determine to what extent values recorded in a country are influenced by those in neighbouring countries. Based on the latitude and longitude of the European Union's countries, the matrix of spatial weights  $W$  (spwmat in Stata) was built, which shows the interactions of a state with its neighbours, the spatial gap model was developed (Pisati, 2001) and diagnostic and post-estimation tests for spatial dependence were performed for all analysis models specified in equations 2-6 (using the Moran index, of the Rho spatial coefficient, Wald, Likelihood Ratio and Lagrange Multiplier tests):

$$y = \rho Wy + \beta X + e \quad (1)$$

in which  $\rho$  is the autoregressive spatial dependence parameter,  $Wy$  is the spatial lag of the dependent variable  $y$ ,  $X$  represents the independent variables, and  $e$  shows the errors.

The core explanatory variable of this study captures the application of artificial intelligence technologies in enterprises, by the percentage of large enterprises, which have 250 or more employees, and which use artificial intelligence technologies in production activity (AI\_PROD\_LARGE), (Eurostat, 2023f). The influence of the application of artificial intelligence in enterprises on economic growth is studied using the dependent variable GDPPP (euro) - Gross Domestic Product per capita, expressed in euro / person, at market prices (reference 2010), (Eurostat, 2023a). To capture the social impact of the application of artificial intelligence in enterprises, welfare phenomena and social disparities are targeted, and four distinct dependent variables are used:

- Average net income per person (annual), (INCOMEPP - Euro/person), (Eurostat, 2023b), captures the average income of the population in the EU.
- People at risk of poverty or social exclusion (POVERTY - Thousand people), (Eurostat, 2023c), groups individuals living in households with very low work intensity (less than 20% of the available time in the last 12 months), with an equivalent total disposable income below the threshold of 60% of the national median income and are in severe material deprivation (Guio et al., 2021).
- The at-risk-of-poverty threshold indicator (THRESHOLD, expressed in the Purchasing Power Standard) (Eurostat, 2023d) is set at 60% of the median equivalised disposable income



at national level, after social transfers and refers to a household of two adults and two children under 14 years of age (Guio et al., 2021).

- The annual unemployment rate (UNEMPL), expressed as a percentage, captures the percentage of people looking for a job (Eurostat, 2023e).

The control variables used in the analysis models are the following: Gross domestic expenditure on research and development by the higher education system, expressed in millions at the Purchasing Power Standard (R&D\_EXPENSES), (Eurostat, 2023g); Government expenditure on education, expressed as a percentage of Gross Domestic Product (EDUC\_EXPENSES), (World Bank, 2023); Education, represented by the average of school years, expressed in years (EDUCATION) (United Nations Development Programme, 2023); Labour productivity per person employed, percentage of EU-27 total (2020 reference based on Purchasing Power Standard million, current prices), (LABPRODPP), (Eurostat, 2023h); Sum of exports and imports of goods and services, measured as a share of Gross Domestic Product (TRADE), (World Bank, 2023); Inflation, annual consumer price index, expressed as a percentage (INFLA), (World Bank, 2023); GINI coefficient of disposable income inequality, scale from 0 to 100 (GINI), (Eurostat, 2023i); Annual growth in government spending, based on constant local currency and expressed as a percentage (GOVEXPG), (World Bank, 2023); Life expectancy at birth, expressed in years (LIFEEXP), (United Nations Development Programme, 2023); Patent applications, residents, expressed in absolute values (PATENTS), (World Bank, 2023); Tax burden (TAX\_BURDEN), as total tax revenue relative to GDP / % of GDP (Heritage Foundation, 2023).

To study the influence of the implementation of artificial intelligence in enterprises on economic growth, welfare, and social disparities in the EU, the following models of multiple linear regression are developed. In equations 2-6, indicators of economic growth, welfare and social disparities are alternatively considered as dependent variables of the model, as follows:

$$GDPPP(\text{euro})_{i,t} = \alpha_0 + \alpha_1 \text{AI\_PROD\_LARGE}_{i,t} + \alpha_2 \text{R\&D\_EXPENSES}_{i,t} + \alpha_3 \text{EDUCATION}_{i,t} + \alpha_4 \text{LABPRODPP}_{i,t} + \alpha_5 \text{TRADE}_{i,t} + \alpha_6 \text{INFLA}_{i,t} + u_{i,t} \quad (2)$$

$$\text{INCOMEPP}_{i,t} = \alpha_0 + \alpha_1 \text{AI\_PROD\_LARGE}_{i,t} + \alpha_2 \text{R\&D\_EXPENSES}_{i,t} + \alpha_3 \text{EDUC\_EXPENSES}_{i,t} + \alpha_4 \text{EDUCATION}_{i,t} + \alpha_5 \text{LABPRODPP}_{i,t} + \alpha_6 \text{TRADE}_{i,t} + \alpha_7 \text{INFLA}_{i,t} + \alpha_8 \text{GINI}_{i,t} + u_{i,t} \quad (3)$$

$$\text{POVERTY}_{i,t} = \alpha_0 + \alpha_1 \text{AI\_PROD\_LARGE}_{i,t} + \alpha_2 \text{R\&D\_EXPENSES}_{i,t} + \alpha_3 \text{EDUC\_EXPENSES}_{i,t} + \alpha_4 \text{EDUCATION}_{i,t} + \alpha_5 \text{TRADE}_{i,t} + \alpha_6 \text{INFLA}_{i,t} + u_{i,t} \quad (4)$$

$$\text{THRESHOLD}_{i,t} = \alpha_0 + \alpha_1 \text{AI\_PROD\_LARGE}_{i,t} + \alpha_2 \text{R\&D\_EXPENSES}_{i,t} + \alpha_3 \text{EDUCATION}_{i,t} + \alpha_4 \text{TRADE}_{i,t} + \alpha_5 \text{GINI}_{i,t} + \alpha_6 \text{GOVEXPG}_{i,t} + \alpha_7 \text{LIFEEXP}_{i,t} + u_{i,t} \quad (5)$$

$$\text{UNEMPL}_{i,t} = \alpha_0 + \alpha_1 \text{AI\_PROD\_LARGE}_{i,t} + \alpha_2 \text{PATENTS}_{i,t} + \alpha_3 \text{EDUCATION}_{i,t} + \alpha_4 \text{GDPPP}(\text{euro})_{i,t} + \alpha_5 \text{GOVEXPG}_{i,t} + \alpha_6 \text{TRADE}_{i,t} + \alpha_7 \text{TAX\_BURDEN}_{i,t} + u_{i,t} \quad (6)$$

where  $i$  represents the country,  $t$  is the year,  $\alpha_0$  is constant (intercept),  $\alpha_{1,2,3,4,5,6,7,8}$  are the coefficients of the estimated parameters, and  $u_{i,t}$  is the error. Data collected at the European Union level are processed econometrically in STATA software.

### 3. Results and discussions

The preliminary analysis of the data was performed based on the classical assumptions of regression models: multicollinearity (resulting in the absence of multicollinearity from correlation matrices), homoscedasticity (identified in the studied models, except for the one for unemployment, which shows heteroscedasticity), stationarity (not applicable, given a single year of analysis) and normality of errors (according to which the logarithmic forms of the variables used in estimate). To study endogeneity, the Durbin-Wu-Hausman test (Table No. 1) was applied and compared with the critical value of the chi-squared distribution, for which the number of degrees of freedom was determined to be equal to the number of potentially endogenous independent variables in each analysis model. The statistical value of the Durbin-Wu-Hausman test exceeds the critical value, which leads to the rejection of the null hypothesis of exogeneity of variables and indicates the endogeneity of the variables used in the analysis, for all models.

Static analysis of the economic and social impact of the application of artificial intelligence technologies in large enterprises in production activity is carried out using the generalised least squares method (FGLS), according to Table no. 1.

**Table no. 1. Economic and social impact of the use of artificial intelligence in production activity in large enterprises (European Union, 2021)**

VARIABLES	GDPPP (euro)	INCOME P	POVERTY	THRESHOLD	UNEMPL
	model 1.1	model 2.1	model 3.1	model 4.1	model 5.1
AI_PROD _LARGE	0.020* (0.008)	0.023* (0.010)	-0.045** (0.021)	0.024*** (0.004)	-0.289** (0.117)
R&D _EXPENSES	0.105*** (0.030)	0.123*** (0.033)	0.625*** (0.077)	0.059*** (0.017)	-
EDUCATION	0.097*** (0.035)	0.118* (0.047)	-0.301** (0.116)	0.125*** (0.021)	-1.173*** (0.376)
EDUC _EXPENSES	-	0.139** (0.057)	-0.350*** (0.129)	-	-
LABPRODPP	0.009*** (0.001)	0.007*** (0.001)	-	-	-
TRADE	0.001*** (0.001)	0.001* (0.001)	-0.004** (0.001)	0.001*** (0.001)	-0.028*** (0.007)
INFLA	-0.162*** (0.030)	-0.179*** (0.036)	0.212** (0.090)	-	-
GINI	-	0.027*** (0.009)	-	0.026*** (0.005)	-
GOVEXPG	-	-	-	0.044*** (0.011)	-0.594*** (0.222)
LIFEEXP	-	-	-	0.046*** (0.008)	-
GDPPP (euro)	-	-	-	-	3.637*** (1.198)
PATENTS	-	-	-	-	-0.937*** (0.263)
TAX_BURDEN	-	-	-	-	0.166** (0.068)
Constant	7.278*** (0.420)	5.188*** (0.685)	9.018*** (1.152)	2.897*** (0.775)	-6.586 (11.027)
Durbin-Wu- Hausman test	13.095	9.552	14.705	13.005	8.862
Critical value chi <sup>2</sup>	1.635	2.732	1.635	2.167	2.167

Note: \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ . Standard errors are in parentheses. The variables GDPPP (euro), INCOMEPP, POVERTY, THRESHOLD, R&D\_EXPENSES and PATENTS were used in logarithmic form. Models are developed by Feasible Generalized Least Squares - FGLS.

Spatial analysis of the economic and social impact of applying artificial intelligence technologies in large enterprises in production activity is carried out using the Spatial Lag Model (SLM), according to Table no. 2.

**Table no. 2. Spatial analysis of the economic and social impact of the use of artificial intelligence in production activity in large enterprises (European Union, 2021)**

VARIABLES	GDPPP (euro)	INCOMEPP	POVERTY	THRESHOLD	UNEMPL
	model 1.2	model 2.2	model 3.2	model 4.2	model 5.2
AI_PROD LARGE	0.027*** (0.007)	0.028*** (0.010)	-0.039* (0.021)	0.024*** (0.005)	-0.260** (0.107)
R&D EXPENSES	0.172*** (0.031)	0.171*** (0.038)	0.634*** (0.075)	0.055** (0.022)	-
EDUCATION	0.082*** (0.030)	0.106** (0.044)	-0.395*** (0.131)	0.126*** (0.021)	-1.662*** (0.411)
EDUC EXPENSES	-	0.149*** (0.053)	-0.394*** (0.128)	-	-
LABPRODPP	0.009*** (0.001)	0.008*** (0.001)	-	-	-
TRADE	0.003*** (0.001)	0.002*** (0.001)	-0.003** (0.001)	0.001*** (0.001)	-0.029*** (0.006)
INFLA	-0.179*** (0.026)	-0.189*** (0.034)	0.201** (0.087)	-	-
GINI	-	0.030*** (0.009)	-	0.026*** (0.005)	-
GOVEXPG	-	-	-	0.043*** (0.011)	-0.436** (0.215)
LIFEEXP	-	-	-	0.046*** (0.008)	-
GDPPP (euro)	-	-	-	-	3.339*** (1.098)
PATENTS	-	-	-	-	-1.079*** (0.248)
TAX_BURDEN	-	-	-	-	0.159** (0.061)
Constant	11.333*** (1.236)	7.904*** (1.492)	11.942*** (2.397)	2.497 (1.560)	6.510 (11.746)
Rho	-0.452*** (0.132)	-0.335** (0.167)	-0.240 (0.174)	0.040 (0.138)	-0.563** (0.263)
Wald test	11.684*** (0.001)	4.043** (0.044)	1.894 (0.169)	0.087 (0.768)	4.566** (0.033)
Likelihood ratio test	9.526*** (0.002)	3.734* (0.053)	1.825 (0.177)	0.087 (0.768)	4.102** (0.043)
Testul Lagrange Multiplier test	8.024*** (0.005)	3.654* (0.056)	1.625 (0.202)	0.094 (0.760)	3.903** (0.048)
Moran test (dependent variable)	0.355*** (0.001)	0.400*** (0.001)	-0.010 (0.386)	0.387*** (0.001)	0.002 (0.329)

Note: \*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ . Standard errors are in parentheses (except for the last four lines, where  $p$ -value signifies). The variables GDPPP (euro), INCOMEPP, POVERTY, THRESHOLD, R&D\_EXPENSES and PATENTS were used in logarithmic form. The analysis is developed through the Spatial Lag Model (SLM).

The results obtained in static models for testing the influence of AI from large enterprises in production activity on the economy and society are statistically significant for all studied variables (models 1.1, 2.1, 3.1, 4.1 and 5.1, Table no. 1). The interpretation of the coefficients in a static approach, based on the data available for 2021, focusses on the analysis of the meaning, respectively, of the significance of the influence and less on a quantitative interpretation of the value of the estimation coefficients obtained.

On average, increasing the percentage of large enterprises using AI in their production activity leads to economic growth in the member states of the European Union (given that the rest of the analysed variables would remain constant, model 1.1, Table no. 1), which leads to *acceptance of the H<sub>1</sub> hypothesis*. Mechanisms that contribute to economic growth lie in the potential of artificial intelligence applied to companies to increase productivity and reduce costs, especially through automation (Polak et al., 2021b), as well as to contribute to the production of new goods and services conducive to economic growth through innovation processes (Yugang, 2019). Also, while artificial intelligence can lead to the disappearance of certain jobs, it can contribute to the development of new occupations and jobs generating economic growth (Haiss, Mahlberg and Michlits, 2021).

The results obtained for *the control variables* used in the analysis are in line with those of the previous literature. Research and development spending in higher education systems and enterprises increases innovative capacity and productivity (Czarnitzki, Fernández and Rammer, 2023), contributing to economic growth (Dong et al., 2020; Gardiner and Hajek, 2023). Education catalyses economic growth through mechanisms to improve the quality of human capital and labour productivity (Habibi and Zabardast, 2020). Trade is the driving force behind economic growth, especially at higher levels of development in the productivity of factors of production (labour and capital) (Ramzan et al., 2019). Regarding inflation, there is evidence of a negative relationship between inflation and economic growth, amid discouragement to investment, higher wages, and reduced corporate profits, and the threshold level of inflation that could contribute to economic growth is controversial (Akinsola and Odhiambo, 2017).

Analysis of the influence of AI on variables that capture well-being and social disparities shows that, on average, the increase in the percentage of large enterprises using AI in their production activity leads to an increase in the average net income per person, respectively, in the poverty line, and to a decrease in the number of people at risk of poverty and unemployment in Member States of the European Union (provided that the rest of the analysed variables would remain constant, models 2.1, 3.1, 4.1 and 5.1, Table no. 1). The results obtained lead to *partial acceptance of the H<sub>2</sub> hypothesis*. The models developed in this study show that the application of AI in enterprises leads to an increase in average net income per person (invalidated hypothesis), a decrease in the number of people at risk of poverty or social exclusion (invalidated hypothesis), and to a decrease in unemployment (invalidated hypothesis). Under the impact of AI application in companies, the poverty threshold is increasing, which shows that the threshold at which the poverty threshold is assessed becomes higher (validated hypothesis), and if people's incomes did not increase, then more people could be at risk of poverty and social exclusion. Fortunately, the application of AI in businesses has the potential to contribute to an increase in average net income per person, which mitigates the effects on the previously rendered poverty line.

The increase in average net income per person (Model 2.1) under the impact of AI technologies in enterprises may manifest itself either as a result of higher wages of highly

qualified employees operating AI technologies (Peralta-Alva and Roitman, 2018; Lu, 2022), or is the result of productivity effects, capital accumulation and creation of new tasks and jobs specific to human employees in AI-impregnated environments, which contribute to increased employee remuneration, a phenomenon that is superior in salary intensity to the effects of employee replacement by AI technologies (Fossen, Samaan and Sorgner, 2022).

The decrease in the absolute number of people at risk of poverty as a result of the impact of applying AI technologies in companies (model 3.1) is explained by the effects of AI technologies on productivity growth, accompanied by wage growth (Sipola, Saunila and Ukko, 2023), by the potential of AI to stimulate the workforce in developing new skills, which allow higher income for more skilled work (Haiss, Mahlberg and Michlits, 2021; Polak et al., 2021b), through the role AI plays in innovation, supporting entrepreneurial activities, accessing new markets, and creating jobs, generating additional income for both capital holders and employees (Pansera and Martinez, 2017; Yugang, 2019).

The increase in the poverty line as a result of technological progress and the proliferation of AI technologies in companies (model 4.1) is the result of higher earnings or capital holders, which generates a higher value of the earnings limit on the basis of which the poverty threshold is set, so that people who do not reach the level of earnings at the limit of this analysed threshold will be at risk of poverty or social exclusion (Pansera and Martinez, 2017; Acemoglu and Restrepo, 2019; Lu, 2022).

The estimated decrease in unemployment under the impact of AI technologies in enterprises (model 5.1) lies mainly in the potential of these technologies to contribute to the creation of new jobs or occupations, which require more advanced knowledge of workers to operate the technological facilities implemented or which cannot be automated (Haiss, Mahlberg and Michlits, 2021; Mutascu, 2021).

The results obtained for *the control variables* are consistent with previous literature in the field: government spending contributes to poverty reduction (Saharudin et al., 2023), R&D spending in the higher education system, education expenditure, average school years (Gardiner and Hajek, 2023), trade, labour productivity (Ramzan et al., 2019), life expectancy at birth and decreasing income inequality (Regidor et al., 2003), respectively, inflation (Mutascu, 2021), while the unemployment rate is influenced by the average of school years, trade, government spending, economic growth, patents and tax burden (Flaig and Rottmann, 2013; Odhiambo, 2015; Hjazeen, Seraj and Ozdeser, 2021; Mutascu, 2021).

The spatial analysis to test the influence of AI from large enterprises in production activity on the economy and society is mixed (Models 1.2, 2.2, 3.2, 4.2 and 5.2, Table no. 2), given that statistical significance is present only for models 1.2 and 2.2. In the Spatial Lag Model, which uses the average value of the dependent variable for neighbouring countries, the robustness of spatial diagnosis tests (based on Moran's index) and post-estimation tests (based on Rho spatial coefficient, Wald, Likelihood Ratio and Lagrange Multiplier tests) shows that there are effects of the dependent variable (economic growth and average income per person) of neighbouring countries on these indicators in the country of origin studied, respectively, that there is spatial autocorrelation in the models. The negative values of the spatial coefficient Rho indicate that neighbouring values have a negative influence on the current value, and based on the positive Moran's index, it follows that similar values tend to group together (Pisati, 2001). The positive coefficients obtained in both models for the basic explanatory variable (application of AI in large enterprises) show that increasing the degree

of AI implementation in enterprises in one country leads to economic growth (Model 1.2) or to an increase in average income per person (Model no. 2.2) in neighbouring countries, provided that the rest of the model variables do not change. While there is a positive effect of the basic explanatory variable because negative spatial autocorrelation ( $\rho$ ) manifests itself, the latter counteracts and offsets some of the positive effect of AI in a country on economic growth or average income per person in neighbouring countries.

The development of AI technologies in large enterprises in European Union states leads to economic growth in neighbouring states through spillover or contagion effects, generated by scientific and technological innovation, exchange of information between regions, mobility of human and technological capital (Li et al., 2022). As neighbouring countries implement AI in production activity and increase labour productivity, trade relations, distribution and supply chains with partners from neighbouring states are developed or streamlined, contributing to the expansion and efficiency of cross-border business (Ghobakhloo et al., 2023) or labour is attracted from the neighbouring country (Graglia and Von Huelsen, 2020), which indirectly generates economic growth and well-being.

The  $H_3$  hypothesis is partially accepted, given that models 1.2 and 2.2 are robust and denote spatial dependence between the implementation of AI in enterprises in one European Union state and economic growth or average income per person in neighbouring states, while the rest of the models show mixed results. Models 3.2 and 4.2 (dependent variables number of people at risk of poverty and poverty threshold, respectively) do not receive significant results for spatial dependence or post-estimation tests, while model 5.2 (dependent variable unemployment rate) shows significant results for post-estimation tests, but spatial dependence based on the Moran's index is not confirmed.

Despite the mixed results obtained in the spatial analysis, amid the small number of years of observation, the confirmed results for the first two models analysed give indications of how the transformation of enterprises in neighbouring countries in terms of AI deployment has the potential to produce contagion, demonstration and imitation effects from one country to another, contributing to reducing economic and social disparities.

## Conclusions

Against the background of the literature gap in the field of implementation of artificial intelligence in businesses, this study uses the only complete set of statistical data available at the EU level for the year 2021 and which groups information on the percentage of enterprises that use artificial intelligence technologies in production activity. Regression and spatial models analyse the effects of the application of artificial intelligence in companies on economic growth, welfare, and social disparities.

The results are in line with the previous literature and suggest the positive impact of the application of artificial intelligence in enterprises on economic growth, explained by the innovative potential of artificial intelligence in enterprises, generating new goods and services, leading to economic growth. Artificial intelligence in companies increases productivity, reduces costs, in particular through automation, and even though it may lead to the disappearance of certain jobs, it has the potential to develop new growth-generating occupations and jobs. The findings on the influence of artificial intelligence in enterprises on welfare and social disparities show mixed results: increasing the average net income per

person, respectively, the poverty threshold, and decreasing the number of people at risk of poverty and unemployment. These empirical results do not validate the mainstream media or some specialised studies that underline the devastating role of artificial intelligence in social and individual welfare.

The spatial analysis of spatial spillover and contagion relations at the level of European Union states identifies positive effects of the implementation of artificial intelligence in enterprises in a country on economic growth and average income per person in neighbouring countries. Scientific and technological innovation, exchange of information between regions, mobility of human and technological capital, development of trade relations between states, and labour mobility generated by the implementation of artificial intelligence in enterprises in a state contribute to economic growth and welfare in neighbouring states.

From a theoretical perspective, the present study has implications for the management of enterprises implementing artificial intelligence technologies, while, from a managerial perspective, respectively, of public policies, the paper highlights the need for a systemic approach to legislative packages specific to artificial intelligence technologies.

An important limitation of the study is that it uses data related to a single year of analysis, 2021 and analyses only the countries of the European Union. An extension of the number of years studied would allow the use of dynamic panel analysis methods, whose results are more reliable than those obtained by linear regression models or spatial analysis, and exploring other states or regions could lead to relevant results.

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