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ARTIFICIAL INTELLIGENCE AS A DRIVER OF INNOVATION AND PATENT ACTIVITY: AN EMPIRICAL ANALYSIS OF CROSS-COUNTRY DATA

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ABSTRACT. In the context of accelerated digitalization and the development of artificial intelligence technologies, the impact of AI on innovation and patent activity is becoming especially relevant. This study aims to empirically assess the relationship between various aspects of AI development and indicators of countries' innovative development. The Global Innovation Index and the level of patent activity are used as dependent variables, while investments in AI, publications, the number of new AI companies, and the aggregated AI rating serve as explanatory variables, along with control variables. The analysis used data for 36 countries for 2017-2023, and the panel regression method with fixed and random effects. The results show that publication activity and the number of AI companies have a positive and statistically significant impact on the GII index, while institutional factors – Human Development Index and R&D expenditures – contribute to the growth of patent activity. The findings also highlight the complex and context-dependent impact of aggregated AI ratings and investment levels, which appear to be influenced by each country's underlying economic structure and institutional quality. These results are in line with contemporary empirical research and point to the need for adaptive, well-targeted policy strategies that recognize AI's potential as a driver of innovation and technological transformation, while accounting for national development contexts.

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Introduction

In the context of rapid digitalization and global technological competition, artificial intelligence is becoming one of the key factors in transforming economic systems. Its implementation has an increasingly significant impact on production processes, management, scientific research, and decision-making (Mariani et al., 2023; Cockburn et al., 2018; Pietronudo et al., 2022). Modern AI technologies are being actively implemented not only in high-tech industries but also in more traditional sectors of the economy, helping to accelerate the innovation cycle and increase the competitiveness of national economies (Makridakis, 2017; Akter et al., 2023). At the same time, the scientific community is showing growing interest in studying the impact of AI on the structural characteristics of economic development, including innovative activity and technological performance of countries (Haefner et al., 2021; Li et al., 2023; Fredström et al., 2021; Igna & Venturini, 2023). Emerging economies face particular challenges in realizing AI's potential for economic growth, as research demonstrates that successful AI implementation requires complementary human capital development and strategic integration across manufacturing and service sectors to achieve meaningful productivity gains (Sarker, 2022). A growing body of research explores the relationship between artificial intelligence and various innovation and technological advancement indicators. For instance, Igna & Venturini (2023) examine patent data across European companies and find that firms' prior ICT innovations and internal R&D investments are key drivers of AI innovation. They also emphasize the importance of institutional factors in enabling AI adoption. Similarly, Fredström et al. (2021) apply AI-based methods to analyze large-scale patent datasets and propose a research agenda for understanding AI's broader impact on technological development. Mariani et al. (2023) conduct a systematic literature review and categorize types of AI-driven innovation, highlighting the need for quantitative assessments at the national and sectoral levels.

Despite these contributions, a notable research gap remains in developing integrated empirical models that account for publication activity, institutional readiness, and investment in AI to innovation and patent performance. Reviews by Mariani et al. (2023) and Fredström et al. (2021) explicitly stress the lack of comprehensive quantitative analyses, particularly in the context of emerging economies where empirical data remain scarce.

In response to this gap, this study seeks to empirically investigate how artificial intelligence activity influences the innovative performance of countries, with a particular focus on patent productivity. The analysis incorporates key socio-economic and institutional variables to capture the broader context of technological development. Specifically, the paper tests two hypotheses: (1) higher levels of AI activity are positively associated with enhanced innovative performance, and (2) the adoption of AI technologies leads to an increase in patent output.

The analysis is based on panel data from 36 countries spanning the years 2017 to 2023, utilizing regression analysis methods with both fixed and random effects. The time interval covers a key stage in forming the global AI agenda and allows us to identify cross-country differences in the effectiveness of AI policies.

The article's structure includes the following sections. The first section provides an overview of the modern scientific literature on AI's impact on innovation and intellectual property. The second section describes the research methodology, including data sources, model specification, and diagnostic procedures. The third section presents the results of the

panel analysis, which aims to test the two hypotheses put forward, interpret the obtained results, and discuss their significance from the standpoint of applied economic policy. The article concludes with conclusions and proposals for further research directions.

1. Literature review

Current research demonstrates that AI has a powerful and multi-level impact on organizations and countries' innovation and patent activity (Tekic & Füller, 2023; Kakatkar et al., 2020; Just, 2024). AI significantly gains productivity at the innovation level, especially when idea generation, data analysis, and prototyping can be automated. For example, a study by Toner-Rodgers (2024) demonstrated that implementing AI in a large US research laboratory resulted in a 44% increase in new material discoveries, a 39% increase in patent applications, and a 17% increase in product innovation. At the same time, there is an uneven effect depending on the staff's skill level: top researchers demonstrated a sharp increase in productivity, while less experienced employees reported a decrease in job satisfaction and creative engagement. Similar effects are confirmed by other empirical studies (Rammer et al., 2022; Kozhakhmetova et al., 2024), which found a positive correlation between the maturity of AI implementation and innovation performance, in particular, increased sales from “global firsts” and cost reduction, using German companies as an example.

AI is actively used at various stages of the innovation cycle, from idea generation (Toner-Rodgers, 2024) and product development (Roberts & Candi, 2024) to process evaluation and optimization. Employees perceive generative AI systems such as ChatGPT as more satisfying than traditional AI tools and are directly associated with increased innovation performance.

Regarding patent activity, there has been an exponential increase in AI-related applications. Several studies have documented a tenfold increase in patents in digital pathology (Ailia et al., 2022), with applications growing by 30–48% annually in the 2010s (Liu et al., 2021). Between 2002 and 2018, the number of AI-related applications in the United States doubled. China currently leads the way, accounting for 41.2% of all global applications in this area, followed by the United States and Japan (20% each), while Europe has seen growth of between 10% and 25% depending on the source. In addition, South Korea is firmly established in AI in healthcare, while Brazil is lagging due to institutional barriers (World Intellectual Property Indicators, 2024). Technologically, AI patents cover many areas, including machine learning, deep learning, natural language processing, and neural network architecture.

The application of AI goes far beyond the IT sphere: patent activities are recorded in healthcare, manufacturing, telecommunications, and intellectual property law. AI implementation demonstrates significant sectoral variations in performance outcomes, with evidence from logistics and warehouse operations showing measurable improvements in operational efficiency and performance metrics when artificial intelligence technologies are strategically integrated into existing systems (Angamma & Jayawardena, 2022). AI is also becoming a tool in the patent process itself – for example, it is used to speed up prior art searches, assess novelty, and even generate application texts (Vaish et al., 2023; Shomee et al., 2024). From an economic point of view, AI patenting positively impacts labor productivity, especially in small and medium-sized businesses, and helps optimize the costs of innovation processes (Damioli et al., 2021).

Artificial intelligence is increasingly recognized as a transformative force in the innovative capabilities of organizations, not only by enhancing their technological competence but also by reshaping internal structures and innovation processes. AI enables firms to process

vast volumes of data, identify patterns, and generate insights that accelerate R&D cycles and product development (Borges et al., 2020; Haefner et al., 2021). Studies show that AI tools facilitate "recombinant growth", whereby new ideas emerge from unexpected intersections of knowledge domains, improving the creative problem-solving capacity of teams (Agrawal et al., 2018; Bianchini et al., 2022). Beyond technological gains, AI influences organizational routines and decision-making processes, supporting the emergence of autonomous innovation systems and new business models (Sjödén et al., 2021; Fuller et al., 2019). This transition is supported by empirical evidence indicating that AI adoption leads to more decentralized and adaptive decision-making structures (Shrestha et al., 2019; von Krogh, 2018). Moreover, firms increasingly integrate AI into innovation management systems, redefining roles, workflows, and strategic planning mechanisms (Füller et al., 2022; Mariani et al., 2023). New empirical evidence highlights AI's capability to reshape patterns of knowledge creation and strategic decision frameworks across organizations. Specifically, Kaczorowska Spsychalska et al. (2024) demonstrate how generative AI is redefining the foundations of knowledge management, automating tasks, delivering disruptive innovation, and reconfiguring organizational learning paradigms. Gama & Magistretti (2023) introduce a distinction between the "enabling capabilities" required to start working with AI and the "enhancing capabilities" that emerge as a result of the successful application of AI. In addition to firm-level effects, broader institutional and collaborative dimensions are emerging from research in socio-economic disciplines. For instance, Samoilkova et al. (2023) highlight the critical role of university–industry collaboration in R&D, showcasing how context-intervention-outcome mechanisms drive innovation and technological development within cluster ecosystems. As such, AI acts as both a technological enabler and a catalyst for organizational transformation, positioning it at the core of next-generation innovation ecosystems.

Despite the transformative potential of AI, several well-documented challenges persist, including reduced human creativity in decision-making processes, over-reliance on automation without adequate critical oversight, and increased organizational strain due to the continuous need for employee reskilling and adaptation of managerial structures. Lou & Wu (2020) note that AI is less effective in creating radically new products without precedents. Bécue et al. (2024) warn that the impact of AI can be not only synergistic but also destructive if it is not aligned with the company's strategy, the organization's age, and the maturity of its digital technologies. The legal and institutional sphere also faces new challenges. Although the current legal framework is generally considered adequate, experts emphasize the need to adapt legislation, including improving the training of experts, standards for the disclosure of technical information, and harmonizing regulations across jurisdictions. These challenges are particularly acute in developing countries, where legal uncertainty constrains domestic innovation activity (Straus, 2021; Kalmakova et al., 2021; Machado & Winter, 2023). From another angle, regional studies demonstrate how socio-economic tools such as digital transformation models can optimize socio-economic outcomes. Gavurova et al. (2025), for example, developed a hybrid decision support model using fuzzy logic to assess the socio-economic impact of digitalization in tourism across the Visegrad countries, underscoring the role of technological adaptation – potentially including AI tools – in enhancing regional competitiveness and development.

Thus, AI has a transformative impact on innovation and patenting activities, increasing efficiency, expanding the boundaries of applicability, and stimulating organizational development. However, the success of this transformation depends on several factors, including the maturity of AI systems, the strategic flexibility of companies, the quality of the legal environment, and the availability of subject-matter expertise. In parallel, other strands of research highlight the governance potential of AI and its ability to serve as a regulatory tool in institutional environments. For instance, Lyeonov et al. (2024) demonstrate how AI-driven

systems are increasingly used to detect and prevent illegal financial operations. Building on this, Lyeonov et al. (2025) provide empirical evidence of an inverted U-shaped relationship between AI adoption and anti-money laundering effectiveness, revealing that while moderate AI integration enhances AML performance, excessive adoption may introduce systemic vulnerabilities exploitable by financial criminals.

Despite the diversity of approaches, significant gaps remain in the literature. First, few studies empirically assess the relationship between AI activity (investments, publications, institutional conditions) and objective indicators of innovation development, such as the innovation index or the number of patent applications. Second, there is a lack of comparative studies across countries with different levels of development, which prevents generalizations. Third, it is still unclear which types of AI activity – academic, investment, or political-institutional – are most effective regarding technological progress. Moreover, bibliometric studies such as Bilan et al. (2022) and Knapińska & Woźniak Jasińska (2024) emphasize the fragmented nature of current AI and innovation research, noting that more comparative, cross-disciplinary, and policy-relevant analyses are needed to map AI’s long-term institutional effects on innovation outcomes. These gaps justify the need for further quantitative cross-country studies, which is the goal of this article.

2. Methodological approach

This study uses a panel data regression approach to empirically assess the relationship between AI-related activity and countries' innovation and patent performance. The methodology is based on fixed and random effects models, allowing us to account for heterogeneity across countries and over time. The indicators presented in *Table 1* were selected to study the relationship between artificial intelligence and innovative development.

Table 1. Variables for panel data analysis

| Variable | Designation | Justification for inclusion in the model | Source |
|---|-------------------|---|---|
| Dependent variables | | | |
| Global Innovation Index | <i>GII</i> | Reflects the level of innovative development of the country, and is an integral indicator of the effectiveness of innovation policy and environment | WIPO (World Intellectual Property Organization) |
| Total patent applications, units | <i>Patent</i> | Characterizes patent activity as a result of innovative activity and technological maturity | WIPO (World Intellectual Property Organization) |
| Independent variables | | | |
| Global AI Vibrancy Ranking | <i>AI_ranking</i> | A comprehensive index that reflects activity in the field of AI: research, implementation, and ecosystem | Stanford AI Index |
| AI Journal Publications, thousand units | <i>AI_publ</i> | Reflecting scientific activity in the field of AI, publication productivity is one of the factors that contribute to technological innovation. | Center for Security and Emerging Technology |
| Total AI Private Investment, mln \$ | <i>AI_invest</i> | The volume of private investment in AI shows the degree of business involvement in technological development and transformation. | Quid (AI-powered platform) |

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| | | | |
|--|----------------|---|---|
| Newly Funded AI Companies, units | <i>AI_comp</i> | The number of new companies in the field of AI indicates the dynamics of technological entrepreneurship and innovative business. | Quid (AI-powered platform) |
| Control variables | | | |
| Research and development expenditure, % of GDP | <i>R&D</i> | R&D investments form the basis for innovation activity and long-term technological growth. | World Bank Data |
| GDP per capita, current \$ | <i>GDPpc</i> | Reflects the level of economic development and the country's potential to invest in technology | World Bank Data |
| Human Development Index | <i>HDI</i> | A comprehensive indicator of the quality of life, education, and health, influencing the opportunities for the development of human capital and the implementation of innovations | UNDP (United Nations Development Programme) |

Source: *own compilation*

Data were used for 36 countries from 2017 to 2023 for empirical analysis. The choice of the time interval and the countries was due to the need to ensure the completeness, comparability, and representativeness of the data. The Stanford AI Index, one of the most authoritative and regularly updated analytical resources in this field, is the primary source of information on key variables related to the development of artificial intelligence. Since 2017, the annual AI Index reports have presented a comprehensive and stable set of data for countries, using a consistent methodology for collecting information on AI investment, publication activity, and new business creation indicators. 2017 was chosen as the starting point of the analysis, since this is the period from which systematic publication of comparable data by country begins. 2023 is the latest available year at the time of the study, allowing for the maximum expansion of the observation time horizon. The sample encompasses all 36 countries officially represented in the AI Index, ensuring its completeness and providing comprehensive coverage of various regions and models of digital development. This allows for geographic and institutional diversity and correct cross-country comparisons, minimizing possible sample distortions. All countries considered are grouped in *Table 2*.

Table 2. Grouping of countries by the level of development of the innovation and AI ecosystem

| Group of countries | Countries | Classification criteria |
|--|---|--|
| Advanced Innovative Economies | USA, Germany, Japan, UK, France, Canada, Sweden, Switzerland, Netherlands, Finland, Denmark, Austria, Belgium, Norway, Australia, South Korea | High GII and HDI values, developed R&D infrastructure, stable and large-scale private investment in AI, and the maturity of AI ecosystems. |
| Developing Countries with Growing AI Sectors | China, India, Brazil, Mexico, Turkey, Poland, Malaysia, Russia, South Africa, Saudi Arabia | Active dynamics in the number of AI companies, growth of scientific publications, state strategies for digitalization, and technological development |
| Small Digital and High-Tech Economies | Singapore, Estonia, Ireland, Luxembourg, UAE, Israel, New Zealand | High level of digitalization, focus on technology exports, flexibility and adaptability to innovation, high share of IT and AI in the economy |

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| | | |
|---------------------------------|------------------------|---|
| EU Digital Transition Economies | Portugal, Spain, Italy | Active integration into the EU digital agenda, moderate GII and HDI indicators, and stable growth of AI initiatives within the framework of European strategies |
|---------------------------------|------------------------|---|

Source: *own compilation*

The sample includes countries from all major regions of the world – North America, Europe, Asia, Latin America, the Middle East, Oceania, and Africa. These countries have different economic and institutional development levels, allowing us to reflect on the global diversity of models for the implementation and development of artificial intelligence. This approach ensures the representativeness of the sample and the validity of cross-country comparisons within the framework of the empirical analysis.

Table 3. Descriptive statistics

| Variable | Observation | Mean | Standard deviation | Minimum | Maximum |
|-------------------|-------------|----------|--------------------|----------|----------|
| <i>GII</i> | 252 | 49.578 | 9.495 | 29.8 | 68.4 |
| <i>Patent</i> | 252 | 89993.31 | 259993.2 | 196 | 1652437 |
| <i>AI_ranking</i> | 252 | 15.673 | 12.563 | 1.76 | 72.97 |
| <i>AI_publ</i> | 252 | 5.369 | 10.839 | 0.074 | 86.56 |
| <i>AI_invest</i> | 252 | 2037.305 | 8355.988 | 0 | 79560 |
| <i>AI_comp</i> | 252 | 36.44 | 102.293 | 0 | 897 |
| <i>R&D</i> | 252 | 2.08 | 1.183 | 0.258 | 6.019 |
| <i>GDPpc</i> | 252 | 42645.2 | 27479.59 | 1907.043 | 133711.8 |
| <i>HDI</i> | 252 | 0.895 | 0.072 | 0.647 | 0.97 |

Source: *own compilation*

Table 3 presents descriptive statistics to characterize the variables used and provides a preliminary analysis of the data distribution. The sample contains 252 observations corresponding to 36 countries over 7 years (2017-2023), which forms a balanced panel array.

The obtained values indicate significant differences in key parameters in countries' development levels. For example, the average value of the Global Innovation Index is 49.6, varying from 29.8 to 68.4, reflecting a noticeable gap between countries with high and moderate innovation activity. The dispersion in the indicators of private investment in AI (ranging from 0 to 79,560 million dollars) and the number of new AI companies (ranging from 0 to 897) indicates significant differences in the intensity of technological entrepreneurship. There is also a high dispersion in the level of patent activity: from less than 200 to more than 1.6 million patent applications. This confirms the feasibility of using panel methods considering heterogeneity between countries over time. Countries with high values for key variables include the United States, China, Japan, and South Korea, demonstrating a large AI ecosystem and strong institutional support. At the same time, countries such as Estonia, Mexico, and South Africa are characterized by more modest volumes, but are important in terms of regional balance and digital growth prospects.

This study proposes two key research hypotheses about the expected impact of AI activity on innovation development parameters.

Hypothesis 1: AI activity positively affects the level of innovation development of countries.

Hypothesis 2: AI development and implementation contribute to the growth of patent activity, which is one of the direct indicators of technological progress.

A quantitative approach was used to empirically test these hypotheses based on a panel analysis of data for 36 countries from 2017 to 2023. The Global Innovation Index (*GII*) — an integral indicator of innovative development – and the total number of patent applications (*Patent*) are considered alternately as dependent variables. The variables characterizing AI activity are included as key explanatory factors: the AI development index (*AI_ranking*), the number of publications in scientific journals on AI (*AI_publ*), the volume of private investment in AI (*AI_invest*), and the number of newly created AI companies (*AI_comp*). Additionally, the model includes control variables: R&D expenditures, GDP per capita, and the Human Development Index. Fixed and random effects models are used to consider the individual heterogeneity of countries. This allows us to assess the stability and reliability of the results obtained with different model specifications. The models were compared using the Hausman test, which allows us to determine the preference of one of the panel specifications. Additionally, diagnostic procedures were conducted to enhance the reliability of the results, including tests for multicollinearity, autocorrelation, and heteroscedasticity. Results' panel data analysis and related reliability and validity tests were performed using STATA 17.

3. Conducting research and results

At the first stage of the empirical analysis, a check for multicollinearity between the explanatory variables was conducted, since the presence of a high linear relationship between them can distort the estimates of the coefficients in the regression model and affect the interpretability of the results. For this purpose, a correlation matrix of all independent variables was calculated, including indicators characterizing activity in the AI sphere (*AI_ranking*, *AI_publ*, *AI_invest*, *AI_comp*), as well as control variables (*R&D*, *GDPpc*, *HDI*) (*Table 4*).

Table 4. Correlation matrix

| | AI_ranking | AI_publ | AI_invest | AI_comp | R&D | GDPpc | HDI |
|------------|------------|---------|-----------|---------|-------|-------|-----|
| AI_ranking | 1 | | | | | | |
| AI_publ | 0.695 | 1 | | | | | |
| AI_invest | 0.682 | 0.65 | 1 | | | | |
| AI_comp | 0.848 | 0.667 | 0.929 | 1 | | | |
| R&D | 0.246 | 0.175 | 0.218 | 0.265 | 1 | | |
| GDPpc | 0.058 | -0.11 | 0.112 | 0.119 | 0.305 | 1 | |
| HDI | -0.039 | -0.178 | 0.012 | 0.034 | 0.53 | 0.628 | 1 |

Source: *own compilation*

The analysis showed a high correlation between individual pairs of variables, between the volume of private investment in AI and the number of new AI companies, and between the AI activity index and the number of new AI companies. However, most correlation coefficients do not exceed critical values (usually the threshold is 0.8), which allowed us to retain the corresponding variables in the model. In order to ensure the reliability of the estimates and increase the interpretability of the results, these variables were not included simultaneously in one regression specification. Instead, several alternative models were built, each of which included different combinations of explanatory factors with an acceptable level of correlation. The preliminary check provided the basis for a correct model specification and the minimization of potential distortions in the panel analysis results.

Table 5 presents the results of a panel regression estimating the impact of AI activity on the level of innovation performance, measured by the Global Innovation Index (*GII*). Two model specifications were estimated: the first used *AI_ranking* and *AI_invest*, and the second

used *AI_publ* and *AI_comp*. For each specification, the results of both the fixed effects (FE) and random effects (RE) models are presented.

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Table 5. Results of the panel analysis (dependent variable – *GII*)

| Independent variable | I | | II | |
|------------------------|---------------------------------------|----------------------------------|--|---------------------------------|
| | FE | RE | FE | RE |
| <i>AI_ranking</i> | -0.154*** (0.026) | -0.144*** (0.027) | | |
| <i>AI_publ</i> | | | 0.046** (0.026) | 0.036 (0.028) |
| <i>AI_invest</i> | 0.00007*** (0.00002) | 0.00008*** (0.00003) | | |
| <i>AI_comp</i> | | | 0.009** (0.004) | 0.008** (0.004) |
| <i>GDPpc</i> | -0.00008*** (0.00002) | -0.00005** (0.00002) | -0.0001*** (0.00002) | -0.0005** (0.00002) |
| <i>HDI</i> | 30.006** (14.361) | 72.749*** (11.339) | | |
| <i>constant</i> | 28.548** (12.568) | -11.149 (9.785) | 54.147*** (0.865) | 51.282*** (1.506) |
| Number of observations | 252 | 252 | 252 | 252 |
| Number of groups | 36 | 36 | 36 | 36 |
| R ² | 0.256 | 0.295 | 0.254 | 0.128 |
| Test for significance | F(4, 212) = 18.21 [0.0000] | Wald chi2(4) = 71.36 [0.0000] | F(3, 213) = 11.67 [0.0000] | Wald chi2(3) = 9.78 [0.0205] |
| Hausman test | chi2(2) = 7.93 Prob > chi2 = 0.019 | | chi2(3) = 304.67 Prob > chi2 = 0.0000 | |

Notes: 1) in parentheses, there are robust standard regression coefficient errors.

2) **, *** - significance of coefficients at 5% and 1% levels, respectively.

Source: *own compilation*

The results of both models demonstrate a statistically significant impact of the variables reflecting AI activity on innovation performance. In the first model, the *AI_ranking* variable has a negative but significant coefficient (FE: -0.154, $p < 0.01$), which may indicate a complex relationship between the AI ranking and innovation performance. At the same time, the *AI_invest* variable has a positive and significant impact on the *GII* in all specifications (FE: 0.00007, $p < 0.01$), confirming that an increase in private investment in AI is associated with increased innovation performance. In the second model, the variables reflecting scientific and entrepreneurial activity in AI significantly impact *GII*. The *AI_publ* indicator is significant at the 5% level in the fixed effects model (0.046), indicating the importance of the academic component of AI for innovative growth. The number of new AI companies (*AI_comp*) also demonstrates a positive and statistically significant impact (FE: 0.009, $p < 0.05$), confirming the role of technological entrepreneurship in maintaining innovative dynamics.

The control variables exhibit the expected behavior: *GDPpc* has a negative impact, which may indicate the saturation of innovative growth at higher income levels, while *HDI* has a significant positive effect in the first specification (FE: 30.01, $p < 0.05$), emphasizing the importance of human potential for innovation.

The results of the significance tests of the models (Fisher and Wald statistics) show a high overall significance of the equations. In both cases, the Hausman test ($p < 0.05$) confirms that the fixed effects model is preferable, as the differences between the FE and RE estimates are statistically significant. This strengthens the credibility of the findings and highlights the importance of considering individual country effects when assessing the impact of AI on innovative activity. The negative relationship between *AI_ranking* and *GII* found in the model

may be due to the fact that high AI activity does not always lead to an immediate increase in the overall level of innovation development in a country. This may be due to several factors.

First, the impact of AI on innovation productivity may manifest itself with a time lag, since the processes of introducing new technologies, their institutionalization and dissemination in real sectors of the economy take time. Second, AI initiatives may be concentrated in highly specialized industries (e.g., defense, financial technologies, large corporations), which limit their contribution to the overall innovation index, which measures broader parameters, including human capital, business environment, public policy and technological diffusion. Third, a high level of AI activity is not always accompanied by a high quality of the institutional environment, level of education or availability of innovations for small and medium businesses, which also affects the integral GII indicator. Thus, the identified effect may reflect a structural gap between digital development and the maturity of the country's systemic innovation, which requires further study and clarification. Thus, testing the first hypothesis, according to which activity in the field of artificial intelligence contributes to an increase in the level of innovative development of the country, showed partial, but statistically significant confirmation. According to the panel regression results (Table 5), the variables characterizing investment and scientific activity in AI (*AI_invest* and *AI_publ*) have positive and significant coefficients in fixed effects models. An increase in private investment in AI has a stable positive effect on GII, and the number of publications on AI also contributes to the growth of innovative activity, which confirms the importance of the scientific and technological base.

Additionally, the *AI_comp* variable, reflecting the number of newly created AI companies, also has a positive and statistically significant effect on *GII*, emphasizing the role of technological entrepreneurship as a channel for transforming AI initiatives into applied innovations. This result confirms that the creation of new AI companies helps strengthen the country's innovative potential, expanding the practical application of AI technologies in the economy. At the same time, the *AI_ranking* variable, which reflects the overall level of development of the AI sphere, demonstrates a significant negative relationship with *GII*, which may be due to the time lag of the effect, sectoral concentration of AI initiatives, or a structural gap between digital and innovative development. Taken together, the results obtained allow us to conclude that the key components of AI activity – investments, publications, and technological entrepreneurship – positively impact innovative development, thereby supporting *Hypothesis 1*, which receives significant empirical confirmation.

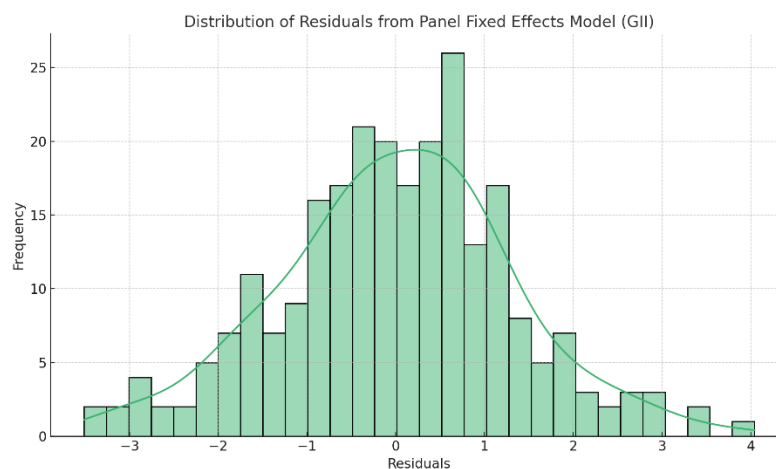


Figure 1. Distribution of residuals of a panel regression model with fixed effects

Source: *own compilation*

Figure 1 shows the distribution of residuals for the fixed-effects model, where *GII* is explained by AI activity indicators (AI ranking, AI investment), GDP per capita, and the human development index, considering country effects. The distribution of residuals is close to symmetrical and concentrated around zero, indicating the absence of serious deviations from the linearity and normality assumptions. This confirms the correctness of the model specification used in the primary analysis.

Diagnostic tests for autocorrelation and heteroscedasticity in panel data were also performed to assess the correctness of the model specification and the reliability of the obtained estimates. The Wooldridge test results did not reveal statistically significant first-order autocorrelation: the F-statistic was 3.892 with p-value = 0.0465. Therefore, the null hypothesis of no autocorrelation is not rejected, and serial dependence of residuals is not observed. Similarly, the Modified Wald test for fixed effects models did not reveal any signs of heteroscedasticity: the null hypothesis of equality of variances between panel units was not rejected at the 5% significance level. Therefore, the residuals of the model can be considered homoscedastic.

Thus, the model satisfies the key assumptions of classical regression, which allows us to rely on the accuracy and stability of the obtained coefficients.

The results of testing hypothesis 2 are presented in Table 6.

Table 6. Results of panel analysis (dependent variable – *Patent*)

| Independent variable | I | | II | |
|------------------------|---|-----------------------------------|--|----------------------------------|
| | FE | RE | FE | RE |
| <i>AI_ranking</i> | -837.814*** (210.834) | -361.833 (286.426) | -2325.183*** (337.388) | -1858.775*** (374.433) |
| <i>AI_publ</i> | 4549.689*** (223.056) | 5070.558*** (304.199) | | |
| <i>AI_invest</i> | -0.946*** (0.221) | -0.995*** (0.304) | | |
| <i>HDI</i> | | | 999626.4*** (191256.2) | 604319.4*** (197568.9) |
| <i>R&D</i> | | | 36645.88*** (8266.509) | 37733.16*** (8983.161) |
| <i>constant</i> | 80623.73*** (3662.17) | 70467.11*** (19685.67) | 844480.2*** (166864.3) | 500244.4*** (174682.9) |
| Number of observations | 252 | 252 | 252 | 252 |
| Number of groups | 36 | 36 | 36 | 36 |
| R ² | 0.761 | 0.8 | 0.275 | 0.266 |
| Test for significance | F(3, 213) = 155.51 [0.0000] | Wald chi2(3) = 292.08 [0.0000] | F(3, 213) = 26.88 [0.0000] | Wald chi2(3) = 46.24 [0.0000] |
| Hausman test | chi2(3) = 12.43 Prob > chi2 = 0.0000 | | chi2(3) = 110.27 Prob > chi2 = 0.0000 | |

Notes: 1) in parentheses, there are robust standard regression coefficient errors;

2) **, *** - significance of coefficients at 5% and 1% levels respectively.

Source: *own compilation*

The results presented in Table 6 demonstrate the impact of AI activity on the level of patent activity measured by the number of patent applications (*Patent*). The first specification of the fixed effects (FE) model includes only the key independent variables of most significant interest in testing the hypothesis: the AI vibrancy ranking (*AI_ranking*), the volume of AI publication activity (*AI_publ*), and the volume of private investment in AI (*AI_invest*). The

variable reflecting the number of new AI companies was not included in the first specification due to high multicollinearity with other indicators, which could distort the model estimates.

Notably, this basic model demonstrated the highest coefficient of determination ($R^2 = 0.761$ for FE and 0.8 for RE), indicating the high explanatory power of the factors included in it. This confirms that the combination of investment, scientific activity, and the overall level of AI development substantially impacts the patent performance of countries. The *AI_ranking* variable, as in the case of the first hypothesis, shows a negative but statistically significant effect on patent activity, which may indicate a time lag between the development of the AI ecosystem and its institutionalization in the formal applications for inventions. At the same time, publication activity (*AI_publ*) has a positive and highly significant effect, confirming the role of scientific developments as one of the primary sources of technological innovation. Investments in AI, on the contrary, demonstrate a negative relationship, which may indicate that at the early stages, private investments are concentrated on pilot projects or applied solutions that do not always lead to immediate patent fixation of the results.

Thus, the first specification of the model allows us to identify the most significant relationships between AI activity and patent productivity of countries, while ensuring a high statistical reliability and interpretability of the results. The second model specification in Table 6 expands the explanatory variables by including additional socio-economic factors: research and development expenditure as a percentage of GDP (*R&D*) and the human development index (*HDI*). This allowed us to assess not only the direct impact of AI activity on patent performance, but also to consider the institutional and resource background within which the innovative development of countries occurs. It should be noted that all included variables turned out to be statistically significant, which indicates the correct specification of the model and the absence of multicollinearity problems in this composition of predictors.

The variables characterizing AI activity retain their influence: the *AI_ranking* remains negatively significant, confirming the observation of a complex, possibly lagged, relationship between systemic AI maturity and entry into the patent stage. The added socio-economic variables behave as expected: R&D expenditures are positively related to the number of patent applications, confirming the key role of institutional scientific infrastructure in technological accumulation. The *HDI* variable also has a positive effect, indicating that more socio-economically developed countries demonstrate higher patent activity, possibly due to the high qualification of human capital.

Thus, the second specification of the model expands the explanatory potential of the analysis by combining AI indicators with systemic macroeconomic and institutional factors. This allows for a deeper understanding of the conditions under which digital transformation facilitates innovative development and technological breakthroughs. Based on the results of the Hausman test presented for both model specifications in Table 6, the following conclusions can be drawn: in the first specification, which includes only the main variables characterizing activity in the field of artificial intelligence (*AI_ranking*, *AI_publ*, *AI_invest*), the Hausman statistic was $\chi^2(3)=12.43$ with $p\text{-value} = 0.0000$. This means that the differences between the estimates of the fixed and random effects models are statistically significant, and therefore, the fixed effects (FE) model is preferable. This result indicates that the sample's country (individual) effects are correlated with the explanatory variables, which violates the assumption of the random effects (RE) model. In the second specification, which additionally considers structural macroeconomic and institutional factors (*R&D*, *HDI*), the value of the Hausman statistic was $\chi^2(3)=110.27$, also with $p\text{-value} = 0.0000$. This also confirms the need for a fixed effects model, since the differences between FE and RE are even more pronounced in this case.

Thus, the Hausman test results for both models indicate that the use of fixed-effects regression is statistically justified and provides correct, unbiased estimates of the influence of factors on patent activity in the panel data structure.

Thus, as a result of testing the second hypothesis, it was found that activity in the field of artificial intelligence has a statistically significant effect on the patent activity of countries. However, the direction of this effect varies depending on the nature of the indicators. Publication activity in AI demonstrates a stable positive effect on the number of patent applications, confirming the role of scientific research as a source of technological innovation. At the same time, the AI development index and the volume of private investment in AI have a negative effect, which may indicate a time lag between the development of the AI ecosystem and the formation of patentable results or reflect the specifics of commercial and non-patentable AI activity. Thus, *Hypothesis 2* about the positive impact of AI implementation on patent activity is partially confirmed.

The obtained results are generally consistent with modern academic research demonstrating the positive impact of AI activity on innovative development and patent productivity. The revealed significance of the variables *AI_invest*, *AI_publ* and *AI_comp* in driving *GII* growth confirms the findings of Toner-Rodgers (2024), who showed that the automation of idea generation using AI leads to an increase in innovation performance, in particular, an increase in the discovery of new materials, the number of patent applications and products. Similarly, the studies of Roberts and Candi (2024) and Rammer et al. (2022) emphasize that mature AI implementation in companies contributes to increased innovation productivity and sales of new products. The positive impact of *AI_publ* on patent activity is consistent with the results of Liu et al. (2021) and Damioli et al. (2021), which show that AI publication activity is closely related to the growth of the number of patents and overall scientific competitiveness. This is especially evident in countries with a developed academic infrastructure, such as the USA, Germany, and Japan.

The presence of a negative relationship between the *AI_ranking* variable and both dependent variables (*GII* and *Patent*) may be due to the fact that the ranking reflects the general level of digital maturity or popularity, rather than actual innovation or patent results. Toner-Rodgers (2024) notes that AI projects at early stages of implementation can decrease employee satisfaction and are not always implemented as patentable solutions, especially when it comes to internal operational processes.

The peculiarities of the investment structure can explain the negative relationship between *AI_invest* and *Patent*. As noted by Shomee et al. (2024) and Vaish et al. (2023), AI is increasingly used in applied tasks – for example, in the automation of patent information searches, application text generation, and expert systems. These areas are not always subject to patenting. In addition, Lou and Wu (2020) highlight that AI is most effective in solutions based on already known mechanisms but shows lower performance in projects with a high degree of novelty. This may also explain the lack of immediate patent effect for AI investments.

The positive impact of HDI and R&D on patent activity is consistent with the results of Gama and Magistretti (2023), Bahoo et al. (2023) and Mariani et al. (2023), who emphasize the importance of institutional and organizational conditions for the successful integration of AI into innovation processes. They point out that a developed research base, government support and a high level of human capital (including digital) form the so-called “enabling capabilities” necessary for transforming AI activity into patents and innovations. The results of the study thus confirm the key findings of the existing empirical literature: AI can enhance both innovation and patenting activity, but the effect is heterogeneous, contextual, and largely dependent on the structure of the economy, the maturity of AI technologies, the scope of application, and institutional conditions. The results also confirm the importance of

distinguishing between short-term and long-term effects and taking into account the time lag between AI investments and measurable innovation outcomes.

These findings have both theoretical and practical implications. From a theoretical perspective, the results contribute to the growing body of literature that explores the relationship between artificial intelligence activity and national innovation performance. The analysis highlights that the intensity of AI-related activity – such as investments, publications, or institutional support – does not automatically translate into effective innovation outcomes. This underscores the importance of examining not only input-level indicators, but also the quality of institutional frameworks and the alignment of AI strategies with broader innovation systems.

From a practical standpoint, the results emphasize that governments and policymakers should go beyond promoting AI development in isolation. Instead, they must ensure that AI initiatives are integrated into national innovation ecosystems, supported by appropriate legal infrastructure, educational frameworks, and industry-academia collaboration. In countries where the level of AI activity is high, but outcomes are limited, attention should be paid to the coordination, governance, and strategic focus of AI-related policies.

In simple terms, the findings suggest that spending more on AI or publishing more AI-related research is not sufficient for achieving higher innovation and patent performance. Countries that align their AI strategies with economic priorities and build supportive ecosystems – through institutional maturity, clear regulations, and effective collaboration – are more likely to see positive results. This implies that policymakers need to monitor not only how much AI activity is happening, but also whether it is producing tangible outcomes such as new technologies, global competitiveness, or productivity gains.

Overall, the study supports the notion that AI acts as both a technological enabler and a catalyst for broader systemic transformation. However, its success depends heavily on contextual factors, including strategic planning, regulatory readiness, and the capacity to translate technological advances into economic and social benefits.

Conclusion

This study confirmed a stable positive relationship between the development of artificial intelligence and countries' level of innovation and patenting activity. Empirical results showed that such indicators as AI investments, scientific publication activity, and the number of new AI companies significantly impact the Global Innovation Index (*GII*) and, to a lesser extent, patent productivity. It was also found that institutional factors – the level of human development (*HDI*) and research expenditure (*R&D*) – play a key role in enhancing the effect of AI. At the same time, negative relationships between specific composite measures of AI activity and the target variables indicate a possible gap between the activity level and its effectiveness, especially in countries with fragmented digital policies. Comparison with existing academic sources confirmed that the effect of AI manifests itself with a time lag and depends on the ecosystem's maturity, the structure of investments, and the scope of AI application.

The results obtained form important guidelines for public policy. First, it is necessary to develop comprehensive AI strategies that include support for both entrepreneurial initiatives and academic science. Second, investments in AI should be accompanied by measures to develop human resources and ensure interaction between universities, R&D structures and businesses. Third, the development of the institutional environment is of priority importance, including an effective system of intellectual property protection, support for patenting and transparent digital regulation. In addition, the policy should consider the time lag between introducing AI and emerging measurable innovative results, providing for sustainable financing and monitoring of long-term effects.

Given the identified time lag, promising areas for future research are building dynamic panel models to assess the delayed effect of AI, spatial analysis of the interrelations between countries and the diffusion of AI technologies, and cross-sector comparative analysis of the sensitivity of innovative activity to various forms of AI. Such studies will enable more accurate determination of the conditions under which AI becomes a driving force for innovative and technological development.

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