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Econometric Modelling of Technological, Environmental, and Structural Drivers of Economic Growth in European Countries

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Abstract: The paper aims to investigate the impact of artificial intelligence, trade, natural resource rents, urbanisation, renewable energy consumption, and industry structure on economic development in selected European countries for the period from 2012 to 2024. By integrating technological, environmental, and structural drivers into a single empirical framework, the study provides a more comprehensive assessment of economic development dynamics than previous research. Given the presence of cross-sectional dependency, heterogeneity, mix-stationarity, and cointegration of the data, the analysis employs different panel models such as Generalised Method of Moments (GMM), Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Dynamic Common Correlated Effects Mean Group estimator (DCCE–MG). The results indicate that artificial intelligence, trade, and natural resource rents have a significant impact on economic development across all applied models. Urbanisation, renewable energy consumption, and industry structure also demonstrate positive effects on economic growth in GMM, FMOLS, and DOLS estimations. Beyond the macroeconomic perspective, the applied models are also relevant for sector-specific contexts. For example, a potential application can be found in the tourism and hospitality sector, where digital transformation, structural characteristics, and environmental factors increasingly shape long-term economic performance. The findings imply that policymakers should promote investments in artificial intelligence, sustainable energy transition, and balanced industrial development in order to strengthen economic growth in

European economies, while the applied modelling framework also provides valuable implications for sector-specific economic policies.

Key words: artificial intelligence investment, panel data, regression analysis, EU24.

1. Introduction

The orientation of technological innovation towards environmental solutions, as a fundamental strategy for enhancing sustainable competitive advantage, alongside the growing role of artificial intelligence (AI), has become a focal point in contemporary research [1]. These innovation dynamics significantly shape the ability of economies to adapt, evolve, and achieve long-term development goals, especially in the context of sustainability-focused growth.

Economic development remains at the centre of these debates, given countries strive to balance expansion of productivity with environmental responsibility and technological advancement. Despite some opinions in the literature that highlight the limitations of traditional GDP-based growth paradigm [2], [3], especially in discussions on well-being and sustainability [4], [5], economic development continues to serve as a core analytical focus in examining how structural, technological and environmental factors interact. Its long-term dynamics are extensively tracked by national and international databases, enabling comparative evaluations and cross-country analyses [6].

While environmental innovation is increasingly recognised as a vital pathway to achieving sustainable growth, contemporary research emphasises the importance of integrating artificial intelligence (AI) into this framework. AI can serve as a significant driver for environmental innovation, particularly in the context of sustainable development for countries with limited economic resources [7]. A combined approach of AI and green technologies offers a strategic advantage which can accelerate the transition to a green economy, provided it is developed in accordance with local technological competencies and policy frameworks.

Understanding the relationship between environmental innovation drivers and economic development has become a central issue in growth strategies. The most commonly analysed environmental innovation drivers are: natural resource rents (NRR), urbanisation (U), and renewable energy consumption (REC). These variables are frequently used in the empirical and theoretical literature examining the relationship between environmental issues and economic growth, particularly their dual influence on environmental change and macroeconomic development. REC is increasingly associated with green growth [8], [9], whereas inadequately managed policy on NRR may reinforce the resource curse and environmental degradation [10]–[12]. Urbanisation is recognised as a key driver of economic transformation, especially when considering smart infrastructure and digital solutions. In academic literature, it is often analysed alongside NRR and REC in the context of economic growth [13], [14].

Economic growth is also shaped by structural factors, particularly trade (TR) and industry structure (IS), which are widely recognised as fundamental determinants of long-term economic development. Khan et al. [15] found that industrialisation, trade, and energy consumption appear to be harmful factors for environmental quality. Trade openness facilitates access to larger markets, improves resource allocation, enhances technology and knowledge transfer, and stimulates competitive pressures and specialisation [16]–[19]. The composition and complexity of industrial structures shape countries' capacity to absorb innovation and adapt to global shifts; whereas, sectoral GDP share is recognised and observed from different aspects in the literature [20]. For example, Carree and Thurik [21] highlighted the importance of industrial structure changes for economic growth, with particular reference to technological change, labour market flexibility, and competition.

Despite extensive research on AI, environmental, and structural factors separately, there is still limited evidence assessing their joint influence on economic development. This study aims to bridge this gap by empirically investigating the comprehensive effects of artificial intelligence (AI), natural resource rents (NRR), renewable energy consumption (REC), urbanisation (U), trade (TR), and industry structure (IS) on economic development (ED). The main contribution of this paper lies in integrating technological, environmental, and structural determinants into a unified empirical framework, thereby providing a broader understanding of the drivers of economic development in European economies. In addition, the study contributes to the literature by applying advanced panel econometric techniques, including GMM, FMOLS, DOLS, and DCCE-MG, which allow for robust estimation in the presence of cross-sectional dependence, heterogeneity, and cointegration. The analysis focuses on 24 EU countries over the period 2012–2024. Initially, the intention was to include all EU member states; however, due to the lack of consistent and available data for certain countries, the final sample was limited to 24 EU economies.

This comprehensive macro-level approach allows for a deeper understanding of economic growth by integrating emerging AI and environmental dynamics while recognising the ongoing importance of structural determinants. These insights become even more valuable when applied from a sector-specific perspective. After COVID-19, the tourism sector was one of the most seriously affected, experiencing unprecedented drops in international arrivals and revenues [22]–[24]. Nevertheless, the evidence indicates that there has been a strong recovery potential, particularly when analysed in relation to the key variables included in the model [25]. Tourism is a sector closely influenced by environmental factors and increasingly dependent on AI-driven innovation [26]–[29]. The variables such as natural resource rents, renewable energy use, and economic development have already been widely utilised in the literature to assess tourism performance and its broader impacts [30]. By incorporating additional determinants such as: Artificial Intelligence (AI), Trade (TR), Urbanisation (U), and Industry Structure (IS), the growth model that has been developed in this paper will be even more comprehensive and holistically applicable to tourism and hospitality [30], [31], [32]. It captures both the sector's vulnerability to shocks and its capacity for rapid transformation driven by digitalisation, sustainability imperatives, and structural change [24], [33]. Velichkovska et al. [34] shows that the adoption of new practices is primarily driven by national policies and institutional support systems, confirming their significant influence on the implementation process.

This paper analyses economic growth through three major dimensions: structural factors, and technological and environmental drivers that reflect the conditions of the contemporary economic environment. The remainder of the paper is organised as follows. Section two presents the theoretical framework and the development of hypotheses. Section three outlines the methodology and specifies the panel econometric techniques employed, including GMM, FMOLS, DOLS, and DCCE–MG. Section four delineates the empirical findings, followed by their discussion in section five. Section six concludes the study, summarising the main findings and providing guidance for future research.

2. Theoretical background

While the role of innovation in boosting growth is widely acknowledged, the main question raised in the literature is how to ensure this growth and make it environmentally sustainable. Environmental degradation has become a significant global issue, worsened by the steady rise in carbon emissions over recent decades [15]. Innovation plays a crucial role in driving the transition to a more resource-efficient economy. Specifically, eco-innovation fosters the development of new technologies, processes, products, services, and business models that are crucial for transforming existing patterns of production and consumption. It promotes energy efficiency and cleaner production methods, which help lower emissions [15]; [35–37]. The adoption of AI introduces new ways which can help improve resource efficiency, support low-carbon transitions, and optimise industrial and urban systems, thereby broadening the traditional understanding of how innovation contributes to economic development [38], [39]. Nevertheless, despite the growing relevance of AI-enabled solutions, classical economic and environmental determinants retain a central role in explaining development patterns, as numerous studies confirm strong causal links between natural resource rents, renewable energy use, urbanisation, and economic performance [8], [13], [39]. At the same time, structural factors, particularly trade openness and industry composition, remain essential for enabling technology diffusion, fostering competition, and enhancing the absorptive capacity of economies [20].

Although numerous studies have investigated individual factors influencing economic development in specific countries, no research has yet examined this relationship in such a comprehensive and multidimensional manner. The existing literature has examined the impact of AI on economic growth across large groups of European countries over relatively long periods, but mostly as a standalone factor [35], [40], [41]. Studies examining environmental drivers usually focus on specific aspects of environmental innovation, often without integrating them with AI or wider structural factors. Research on the structural factors of economic development is plentiful, yet only a few studies jointly analyse the drivers of environmental innovation and AI. Some evidence indicates a multidimensional relationship between digitalisation, natural resources, and trade openness in promoting economic growth [12], while other studies focus either on the role of renewable energy in green economic growth [35], or on the link between natural resource rents and technological innovation [42]. The influence of industrial structure on economic development is well established in economic theory, and scholars have recently also highlighted the importance of policy regulations for renewable energy deployment [43].

Furthermore, recent research has emphasised the interconnectedness between economic growth, technological integration, and environmental sustainability, particularly through the role of ICT development, trade openness, economic complexity, and foreign direct investment in shaping long-term development trajectories [44].

The theoretical framework of this paper is based on endogenous growth theory [45], ecological modernisation theory [46], and the resource curse literature [47], which explain how technological, environmental, and structural factors jointly influence economic development. Endogenous growth theory emphasises the role of technological innovation, knowledge accumulation, and productivity improvements in stimulating long-term economic growth [45], [48]. Ecological modernisation theory highlights the possibility of reconciling economic development and environmental sustainability through technological upgrading, the renewable energy transition, and improvements in resource efficiency [46], [49]. At the same time, from the perspective of the resource curse theory [47], natural resource abundance may negatively affect long-term economic development.

The importance of implementing this type of model in the tourism and hospitality sector is especially significant for post-COVID recovery. The COVID-19 pandemic has tested the resilience of various economic sectors, not only in terms of maintaining profitability but also regarding short-term financial stability. The analysis of companies in Slovakia revealed that the tourism and gastronomy sector suffered the most during the pandemic, particularly when it comes to profitability, due to declining demand, supply chain disruptions, and lockdowns. Nevertheless, the potential of this sector has also been demonstrated, along with its ability to recover quickly once the measures have been relaxed [24]. This forms the basis for the model.

Considering these intertwined technological, environmental, and structural mechanisms within the context of economic development, the line of reasoning forms the foundation for the study’s hypotheses and the development of the conceptual framework.

2.1. The Role of AI Adoption in Economic Development

Technological progress has been acknowledged in literature and practice as a critical factor in fostering economic development. From Schumpeterian theory of creative destruction, through Solow's neoclassical model of technological progress, to Romer's endogenous growth theory, technological innovation has been recognised as a main driver of structural transformation and long-term economic growth [50], [51].

To support this evidence, a bibliometric analysis conducted by Qin et al. [52] has confirmed a growing academic attention regarding the relationship between artificial intelligence (AI) and economic development, addressing certain domains such as intelligent decision-making, social governance, labour and capital, Industry 4.0, and innovation as particularly important. Furthermore, the impact of artificial intelligence (AI) on economic growth has been examined across demographic and social dimensions, underscoring the importance of tailoring AI strategies to a country's development stage [39], [53]. Building on these foundations, Bahoo et al. [40] have expanded the analysis and introduced a conceptual framework to assess how AI adoption can have structurally transformed economic research. Supporting this, the authors Korinek and Stiglitz [54] emphasise the need to rethink traditional economic development because it is unable to capture dynamic AI-driven models. However, the authors unequivocally conclude that AI has a significant impact on economic development, with the strength of its influence varying due to a country's level of development. This aligns with the view that it is of essential importance to make a strategic framework for long-term investments in artificial intelligence and green technologies [55], which has been empirically confirmed by Radulescu et al. [56] on the example of Romania. To support this, Gonzales [50] used panel data across the countries in the period 1970-2019 to show a positive and statistically significant relationship between AI and economic growth. Empirical evidence provided by Abid [48] indicates that AI-driven innovation positively contributes to GDP growth, reinforcing the role of technological advancement in long-term economic development. Similarly, Kalai et al. [41] have investigated the long-term influence of AI on economic development using the ARDL model.

Although the existing empirical research on the environmental impact of technology and innovation provides a solid understanding of how technological progress can support environmental improvement, the environmental benefits of artificial intelligence remain insufficiently understood [57]. In today's dynamic digital landscape, artificial intelligence (AI) is a transformative force reshaping industries and business models, significantly affecting environmental strategies. Its growing use in industries has raised questions about whether these technologies may influence economic performance, and attract considerable scholarly interest [39], [38], [50], [58]. At the same time, countries worldwide are facing increasing pressure for economic growth, which is not only an economic concern but also an environmental one. In this context, Artificial Intelligence (AI) is seen as a powerful tool to boost economic growth by providing innovative solutions across sectors. Moreover, it also presents challenges that may lead to excessive consumption and environmental harm [55], [59]. While the relevant empirical research on the environmental impact of technology and innovation provides a good understanding of how technological innovation can drive environmental progress, environmental benefits of AI remain unclear.

Based on the previous research, the proposed hypothesis is:

H1 *The adoption of artificial intelligence (AI) has a significant impact on economic development.*

2.2. How Environmental Innovation Drivers (NRR, REC and U) Shape Economic Development

Although many countries prioritise environmental sustainability in their policies, the specific roles of drivers of environmental innovation in reaching this goal remain underexplored. Moreover, understanding how nations can balance economic growth with effective environmental protection remains limited. According to OECD/Eurostat [60], innovation with environmental benefits is a new or improved product or process that reduces environmental impacts compared to the enterprise's earlier solutions. These advantages can be the main objective of the innovation or of it's a secondary outcome. Environmental benefits may occur during the production phase or during the use of the product or service by the end user (an individual, another enterprise, the government, etc.).

Understanding the relationship between drivers of environmental innovation and economic development has become essential in the context of sustainable growth strategies. Commonly analysed environmental innovation drivers include natural resource rents (NRR), urbanisation (U), and renewable energy consumption (REC). These variables are often referenced in both empirical and theoretical literature exploring the relationship between environmental issues and economic growth, mainly because of their dual influence on environmental change and macroeconomic performance [46], [49]. From a theoretical perspective, the relationship between environmental innovation drivers and economic development can be interpreted through ecological modernisation theory and resource curse literature. Ecological modernisation theory highlights the possibility of reconciling economic development and environmental sustainability through technological upgrading, renewable energy transition, and improvements in resource efficiency [46], [61]. At the same time, the resource blessing perspective suggests that natural resources may positively contribute to economic growth when supported by strong institutions, effective governance, and productive investment policies [47]. In this context, responsible management of natural resources is essential, especially given their limited availability and the increasingly unsustainable exploitation that often occurs to achieve short-term profits [62]. The relationship between natural resource rents (NRR) and economic development is still subject to academic disagreement in the literature. While some scholars argue that resource wealth promotes growth, others associate it with slower development, commonly known as the "resource curse" [63], [64]. Yu [65] confirms this duality, which shows that the impact of NRR varies across countries and over different timeframes, depending on institutional quality, governance, and policy environment. Positive effects become evident when resource wealth is effectively managed and invested in productive sectors [66], [67], whereas negative effects are linked to volatility, corruption, and economic overdependence [9], [68]. Despite extensive research, findings remain mixed, emphasising the need for more context-specific analyses [69].

Building on the ongoing debate about natural resource rents (NRR) and their complex effects on economic growth, renewable energy consumption (REC) emerges as a crucial supplement and an increasingly significant element in economic development. Furthermore, it is the strategy for attaining a green economic transition as a consequence. Literature often discusses NRR and REC together, exploring how to enhance economic growth while preserving the environment [70], [71]. This relationship is usually conditioned by the context of observation, the level of development of the countries, as well as the observation period. Moreover, given the structural, economic, and institutional differences, the effects of natural resource rents (NRR) and renewable energy consumption (REC) on economic growth can vary substantially across different groups. The increasing severity of environmental issues emphasises the urgent need for effective management of natural resources and greater investment in environmental protection and improvement to reduce the risk of imbalance between resource consumption and their long-term availability [72].

The literature increasingly suggests that the economic effects of natural resource rents are highly conditional upon institutional quality, governance effectiveness, and the capacity of countries to channel resource revenues into productive sectors. In economies with strong institutions, natural resources may function as a "resource blessing", whereas weak institutional environments often reinforce the "resource curse" through corruption, rent-seeking behaviour, and limited economic diversification [73].

For example, Geubrina et al. [63] demonstrated that in ASEAN-5 countries (Indonesia, Malaysia, Thailand, Singapore, and the Philippines) between 2000 and 2020, REC and globalisation contributed positively to sustainable development, while NRR imposed a negative influence due to overexploitation and weak governance structures. These countries are currently facing a critical challenge of balancing rapid development and sustainability, particularly concerning population health [74]. Similarly, Alnsour and Alnsour [75] found that in the Gulf Cooperation Council (GCC) countries (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates), NRRs enhance long-run economic growth, while REC also contributes positively, but independently of NRR. Moreover, economic growth in these countries is driven by capital, labour participation, non-renewable energy use, and trade openness.

An expanding body of empirical evidence supports the view that REC is critical for green economic development. Not only does it contribute to GDP growth, but it also helps decouple economic expansion from environmental degradation. Guliyev [8] confirms a positive long-term effect of REC on economic growth, while Dilanchiev [76] notes that non-renewable energy generally has the opposite effect. Haroon et al. [77] further indicate a bidirectional causal relationship between renewable energy and economic growth across major carbon-emitting nations, with urbanisation and resource rents increasing emissions yet contributing to economic activity.

Hacıimamoğlu and Sandalcılar [78] examined 35 countries (19 of them are developed and 16 of them are developing) regarding renewable energy consumption during the period from 1990 to 2016. They found that in most countries, REC had a positive impact on economic growth when supported by enabling policy frameworks. However, in five countries, REC negatively affected growth mainly due to ongoing reliance on fossil fuels, challenges in grid integration, and slow adoption of renewable technology, emphasising the need for a more gradual and strategic transition. In a final group of countries, no significant link was identified between REC and economic growth, possibly because of the limited integration of renewables into the production process. Their findings highlight the importance of robust renewable energy policies that align with broader development strategies, allowing countries to decouple economic growth from carbon emissions. Similarly, Alkasasbeh et al. [79] highlighted the long-term economic advantages of REC in Jordan and affirmed the argument that investments in REC generate sustainable economic benefits.

In the context of MENA countries (Algeria, Bahrain, Egypt, Iran, Iraq, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Palestine, Qatar, Saudi Arabia, Syria, Tunisia, United Arab Emirates, and Yemen), Nathaniel [13] shows that urbanisation and renewable energy help reduce ecological footprints, while unchecked economic growth tends to exacerbate environmental degradation. Abdulraqeb et al. [80] also note that urbanisation, income, and natural resource dependence in the Middle East are linked to environmental harm, while renewable energy offers a viable path toward green growth. Collectively, these findings emphasise the dual role of these environmental innovative driving factors, such as NRR, REC and U, both as drivers of economic growth and as catalysts or constraints for environmental innovation and sustainability.

Most recent studies agree that REC is positively associated with economic growth, especially in the long run. Nadia et al. [81] employ AMG estimators to support this finding across Asian emerging economies, with additional confirmation from GMM, FMOLS, and DOLS methods. These findings suggest that clean energy investments not only reduce emissions but also generate green jobs, promote industrial diversification, and support long-term sustainability. However, some studies find a negative relationship between REC and growth, potentially due to transition costs [82] and inefficiencies [83].

Urbanisation is widely recognised as a key driver of economic transformation. In the majority of cases, urbanisation has a positive relationship with economic development in resource-based regions, emphasising its vital role in transforming resource-dependent cities and fostering overall economic growth [84]. However, some studies suggest that urbanisation, particularly in Turkey and Romania, along with industrialisation and economic growth, can have a negative impact on environmental quality, mainly due to unbalanced regional development or inefficient urban management practices [85], [86]. Economic and policy influences may be stronger than first expected [87].

Based on all these findings, the proposed hypothesis is:

H2 *The level of environmental innovation drivers in a country has a significant impact on economic development*

2.3. Structural Determinants of Economic Development

The substantial body of empirical literature underscores that structural factors, particularly trade openness and industry structure are crucial in shaping long-term economic development. Numerous studies confirm that increased trade integration improves economic performance through market expansion, optimised resource allocation, knowledge and technology transfer, intensified competitive pressure, and specialisation [18], [88]. Frankel and Romer [89], in one of the foundational contributions, demonstrate that exogenous fluctuations in trade volumes increase income levels, establishing a causal relationship between openness and development. Similarly, Aghion et al. [16] find that international trade positively influences R&D innovation and economic growth, whereas Wacziarg and Welch [18] declare that trade liberalisation consistently elevates growth rates among countries.

Recent studies investigating developing and emerging economies demonstrate similar findings. Khan et al. [90] find that trade openness has a favourable and significant impact on economic growth, while Chabi and Saygılı [17] indicate that trade openness considerably influences the structural transformation of production in ECOWAS nations, reshaping sectoral value-added patterns. Research on transition and post-transition economies also aligns with these conclusions: Shapkova Kocevska and Makrevska Disoska et al. [91], employing OLS panel regressions for Central and Eastern Europe and the Western Balkans, demonstrate that trade is a statistically significant factor influencing economic growth. Country-specific analyses validate a long-term co-integrating relationship between trade openness and economic growth, exemplified by Ali and Pasha [92] in the context of Pakistan. Bakari [12] emphasises the crucial importance of trade openness in fostering growth in East Asia and the Pacific, utilising a Static Gravity Model and GMM estimator at the regional level. The evidence predominantly aligns with the long-term positive impact of openness identified by Wang and Li [11], although they observe that short-term effects may be adverse prior to the realisation of long-term advantages.

Abid [48] shows that AI innovation and trade openness positively influence economic growth in East Asian economies, highlighting the importance of technological progress and international integration. In contrast, gross capital formation has a negative effect, while inflation exerts only a limited influence on growth.

Industry structure, the second structural factor, is also widely acknowledged as one of the key determinants of economic development. Structuralist and neo-Schumpeterian viewpoints emphasise that a strong and diversified industrial base can improve productivity primarily through scale effects, enhanced learning processes, industrial innovations and greater technological intensity [19], [93]–[95].

Empirical studies support these theoretical arguments. For example, Elahinia et al. [96] indicate that manufacturing activity correlates positively with economic growth in European economies, while Haraguchi et al. [97] argue that manufacturing value added can significantly contribute to global GDP, highlighting the sector's pivotal role in productive transformation. Szirmai and Verspagen [98] demonstrate a moderate but favourable impact of manufacturing on economic growth in developing countries, underscoring its significance beyond advanced economies. Additionally, Singh et al. [68] and Khan et al. [99] provide the evidence that manufacturing value added positively influences growth in both advanced and emerging economies, whereas EU-level analyses by Rahim et al. [47] reveal that the economies with more complex and diversified industrial structures show stronger resilience and more robust long-term growth patterns.

Although our study focuses on EU24 countries, the relevance of the above-mentioned structural determinants can also be framed within the tourism sector in general. The economies dependent on tourism increasingly rely on trade openness which facilitates international tourist flows and integration in global service markets. Furthermore, the domestic industries' structure, including tourism-related manufacturing and services, shapes their capacity to absorb technological spillovers, diversify their offers, and shift toward higher-value activities.

Taken together, the previous research consistently supports the view that both trade openness and industry structure are key drivers of economic development. The evidence gathered from causal identification studies, dynamic panel models, and EU-level analyses provides a solid theoretical and empirical background for defining Hypothesis 3.

H3 *Structural factors, such as trade openness and industry structure, significantly influence economic development*

3. Data and Methodology

The variables used in the paper are similar to those in Kwilinski et al. [55] and Wang et al. [64]. The variable Artificial Intelligence (AI) is venture capital (VC) investments in AI and environmental sustainability by country, taken from the OECD website (2025) (Live data from OECD.AI - OECD.AI). The following variables, such as Trade (TR), Natural Resource Rents (NRR), Urbanisation (U), Economic Development (ED), Renewable Energy Consumption (REC), and Industry Structure (IS), were taken from the World Bank website as World Development Indicators (WDI, https://databank.worldbank.org/source/world-development-indicators).

Initially, the aim was to perform an econometric analysis for all countries of the European Union (EU), i.e. for all 27 EU member states. Nevertheless, as some data were unavailable for Bulgaria, the Czech Republic and Malta, it was decided to examine the panel data for the EU24 in the period 2012-2024. Therefore, the panel data for the following EU countries were analysed: Austria, Belgium, Croatia, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, and Sweden. The total number of observations in the panel is 312. Prior to the analysis, the data were logarithmised according to the usual modelling procedure. A more detailed explanation of the variables, their units of measure and the source is displayed in Table 1. The short time dimension (T = 13) is due to data limitations for the AI variable, as a longer and consistent time series was not available for all countries included in the sample. Therefore, the period 2012–2024 was used as a compromise between data availability and the empirical validity of the analysis.

Table 1. Explanations of the used variables

Variables/ Abbreviations	Variables' Name	Explanation	Unit of measure	Source
AI	Artificial Intelligence	VC investments in AI and environmental sustainability by country	in USD millions by country	OECD (2025)
TR	Trade	Trade (% of GDP), measure for trade openness	%	WDI, World Bank
NRR	Natural Resource Rents	Total natural resources rents (% of GDP)	% (share) of GDP	WDI, World Bank
U	Urbanisation	Urban population (% of the total population)	%	WDI, World Bank
ED	Economic Development	GDP per capita (constant 2015 US$)	constant 2015 US$	WDI, World Bank

REC	Renewable Energy Consumption	Renewable energy consumption (% of the total final energy consumption)	% (share) of the final energy consumption	WDI, World Bank
IS	Industry Structure	Manufacturing, value added (% of GDP)	%	WDI, World Bank

Source: Authors' presentation.

Economic Development (ED) was taken as a dependent variable along with six independent variables: Artificial Intelligence (AI), Trade (TR), Natural Resource Rents (NRR), Urbanisation (U), Economic Development (ED), Renewable Energy Consumption (REC), and Industry Structure (IS).

The empirical strategy follows a methodological framework designed to address the specific properties of the panel dataset. First, diagnostic tests were conducted to examine cross-sectional dependence, stationarity, heterogeneity, and cointegration among the variables. Given the dynamic nature of economic development and the potential presence of endogeneity, the Generalised Method of Moments (GMM) estimator was employed to capture short-run dynamic relationships. Since the variables were found to be cointegrated, Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) estimators were subsequently applied to investigate long-run equilibrium relationships among the variables. Finally, the Dynamic Common Correlated Effects Mean Group estimator (DCCE-MG) was used as an additional robustness estimator to account for cross-sectional dependence and heterogeneous slope coefficients across countries.

During the regression analysis, the following panel models were used: Generalised Method of Moments (GMM) by Arellano and Bond [100], Fully Modified Ordinary Least Squares (FMOLS) by Phillips and Moon [101], [102] and Pedroni [103], [104], and Dynamic Ordinary Least Squares (DOLS) by Kao and Chiang [105]. The general or basic versions of the GMM model are described by the equations (1) and (2), whereas the FMOLS and DOLS models are presented by the equations (3) and (4), respectively. Therefore, the GMM is:

$y_{it} = ay_{it-1} + \beta^{'}x_{it} + \mu_i + e_{it}$ (1)

$\Delta y_{it} = a\Delta y_{it-1} + \beta^{'}\Delta x_{it} + \Delta e_{it}$ (2)

Where y_{it} is a dependent variable (in our case lnED) for country *i* (*i*=1, …, N) at time *t* (t=1, …, T), y_{it-1} is the past value of the dependent variable (a dynamic part), a is the coefficient that needs to be estimated, x_{it} is the vector of explanatory variables (in our case lnAI, lnTR, lnNRR, lnU, lnREC, lnIS), $\beta^{'}$are the coefficients with the independent variables that need to be evaluated, μ_i is the unobserved individual effect (fixed effect), while e_{it} is the error term. The differentiation operator is Δ which removes the unobserved effects of μ_i. The GMM model is primarily employed to capture short-run dynamic effects, and to address fixed (unobserved) effects and endogeneity arising from the inclusion of lagged dependent variables.

Panel FMOLS and DOLS are the models described by the following equations, respectively:

$y_{it} = a_i + \beta^{'} x_{it} + u_{it}$ (3)

$y_{it} = a_i + \beta^{'} x_{it} + \sum_{j=-q}^{p} \gamma_{ij} \Delta x_{i,t-j} + e_{it}$ (4)

Where y_{it} is a dependent variable as in the previous case, a_i is an individual effect (a constant that can vary by country), x_{it} is a vector of independent variables,u_{it} and e_{it} are stationary errors in the models, $\beta^{'}$ are coefficients with independent variables that need to be evaluated, Δ is a differentiation operator, and γ_{ij} are coefficients with differentiated variables, p and q are the numbers of future and past lags, while $\Delta x_{i,t-j} = x_{i,t-j} - x_{i,t-j-1}$ is the first difference of an independent variable. With the help of these two models, the long-term cointegration relationship between the variables is examined. FMOLS corrects the standard OLS for endogeneity and serial autocorrelation in cointegration regression and works well with heterogeneous panels, while DOLS performs correction for serial correlation and endogeneity since it adds lags and leads of differentiated variables to the regression. Both models are suitable for smaller sizes (T and N), which is also the case in our study. FMOLS and DOLS estimators are designed to estimate long-run cointegration relationships among variables.

Due to the presence of cross-section dependence, heteroscedasticity, mixed stationarity and the presence of cointegration in the panel data, the model set by Chudik and Pesaran [106] was also evaluated, which is the Dynamic Common Correlated Effects Mean Group estimator (DCCE-MG). DCCE-MG is represented by the following equation:

$y_{it} = a_i + \sum_{p=1}^{P} F_{ip} y_{i,t-p} + \sum_{q=0}^{Q} \beta_{iq}^{'} x_{i,t-q} + \delta_i \Delta \overline{y}_t + \gamma_i^{'} \Delta \overline{x}_t + u_{it}$ (5)

Where y_{it} is a dependent variable (in our case lnED) for country *i* at time *t*, x_{it} is a vector of independent variables, a_i individual (fixed) effects, F_{ip} and $\beta_{iq}^{'}$ are the coefficients measuring dynamic (short-term) effects. The lagged values of the dependent variable are $y_{i,t-p}$, while the lagged values of the explanatory variables are $x_{i,t-q}$. $\overline{y}_t$ is the average of the dependent variable and represents the "common signal" in *y* that changes over time, $\overline{x}_t$ is the average of the independent variable representing the common components in *x*. These averages perform correction for cross-sectional dependence in the panel. δ_i i $\gamma_i^{'}$ are the coefficients on the averages, indicating how much each country *i* reacts to common (global) factors. These coefficients are different for each country. u_{it} is a specific error i.e. a random component which includes noise and factors not explained by the model, and that are country- and time-specific. Δ is the differentiation operator.

4. Results

Table 2 presents a correlation matrix as well as the Variance Inflation Factor (VIF) for checking multicollinearity. Since the VIF factor for all variables is less than 2, it can be concluded that there is no multicollinearity between the variables, therefore we keep all the variables in the model. In most cases, the correlation coefficient is statistically significant and less than 0.5, which can also be interpreted that there is no pronounced multicollinearity between the variables. The exception is the two cases where the correlation coefficient is greater than 0.5 in absolute terms, between lnED and lnNRR (-0.505), and lnED and lnU (0.622), respectively. Interestingly, in Table 2, there is a statistically significant correlation coefficient between economic development and all other observed variables. Furthermore, the correlation coefficients between lnED and lnAI, lnTR, lnU, respectively, are positive and statistically significant at the 0.01 level, while the correlation coefficients between lnED and lnNRR, lnIS, respectively, are negative and statistically significant at the 0.01 level.

Table 2. The Correlation Matrix and Variance Inflation Factor

	lnAI	lnTR	lnNRR	lnU	lnED	lnREC	lnIS	VIF
lnAI	1.000							1.537
lnTR	-0.258*** (-4.694)	1.000						1.221
lnNRR	-0.144*** (-2.564)	-0.168*** (-3.004)	1.000					1.652
lnU	0.349*** (6.555)	0.011 (0.192)	-0.295*** (-5.440)	1.000				1.595
lnED	0.437*** (8.549)	0.274*** (5.016)	-0.505*** (-10.313)	0.622*** (13.978)	1.000			1.814
lnREC	0.024 (0.421)	-0.335*** (-6.268)	0.468*** (9.322)	-0.146*** (-2.607)	-0.194*** (-3.489)	1.000		1.412
lnIS	0.183*** (3.281)	-0.126** (-2.234)	0.431*** (8.409)	-0.422*** (-8.205)	-0.186*** (-3.335)	0.182*** (3.261)	1.000	1.729

Note: ***, ** means that p-value is <0.01, <0.05, respectively. In the brackets, we presented t-stat.

Source: Authors' estimation.

In our case, N is 24 (countries), and T is 13 (the period: 2012-2024), therefore N>T, and for checking cross-sectional dependence in data, the Pesaran [107] test is applied (Table 3), as in Kwilinski et al. [55]. The test is satisfactory when the number of countries (N) is greater than the time dimension (T). In Table 3, it is possible to notice that there is a strong cross-sectional dependence in the data, because the p value in all the cases is less than 0.05. We can conclude, similar to Kwilinski et al. [55], that shocks in one variable are likely to be correlated with the shocks in the other variables across the cross-sections, highlighting the interdependence of these indicators.

Table 3. Test of cross-sectional dependence.

Test/Variables	lnED	lnAI	lnTR	lnNRR	lnU	lnREC	lnIS
Pesaran scaled LM	102.054 (0.000)	34.617 (0.000)	64.990 (0.000)	50.992 (0.000)	106.912 (0.000)	62.925 (0.000)	26.549 (0.000)
Pesaran CD	50.143 (0.000)	27.108 (0.000)	38.670 (0.000)	32.759 (0.000)	40.381 (0.000)	34.449 (0.000)	9.252 (0.000)

Source: Authors' estimation.

After examining cross-sectional dependence in panel data and establishing that the data are cross-sectional dependent, similar to Kwilinski et al. [55], the testing of the stationarity of the data continued using second generation unit root Pesaran's tests [108] (Cross-sectionally Augmented Dickey–Fuller (CADF) and Cross-sectionally Augmented IPS test (CIPS) tests), illustrated in Table 4.

Table 4. Second generation unit root tests

Level						
	CADF			CIPS		
	none	constant	constant & trend	none	constant	constant & trend
lnED	-1.231	-1.337	-1.145	-0.686	-1.200	-1.346
lnAI	-2.816*	-2.305***	-2.761**	-2.919***	-3.462***	-3.513***
lnTR	-2.884**	-1.722	-2.011	-1.002	-1.476	-1.421
lnNRR	-4.736***	-2.312***	-2.401	-1.943***	-3.150***	-2.931***
lnU	-1.379	-1.495	-2.005	-1.657**	-2.724***	-3.619***
lnREC	-1.482	-1.432	-1.217	-1.522*	-2.761***	-2.600*
lnIS	-0.927	-1.722	-2.212	-1.322	-1.399	-2.485
First difference						
ΔlnED	-0.485	-5.238**	-4.727*	-1.911***	-2.529***	-2.963***
ΔlnAI	-5.835***	-2.811***	-2.676**	-4.536***	-4.563***	-4.506***
ΔlnTR	-0.645	-3.592*	-4.978**	-2.146***	-2.323**	-2.659*

ΔlnNRR	-4.182***	-2.065*	-1.835	-4.287***	-4.042***	-3.755***
ΔlnU	-3.560*	-2.570***	-3.341***	-2.229***	-4.033***	-4.403***
ΔlnREC	-3.128**	-2.072*	-3.120***	-4.150***	-3.957***	-4.082***
ΔlnIS	-4.247***	-2.490***	-2.914***	-3.026***	-3.400***	-3.784***

Note: ***, **, * means that p-value is <0.01, <0.05, <0.10, respectively.
Source: Authors' estimation.

Table 4 indicates that the variables ED, TR, and IS are non-stationary at level according to both CADF and CIPS tests, that is, these variables are integrated of order 1, i.e. I(1). The variables U and REC exhibit mixed orders of integration, as they are non-stationary according to the CADF test, whereas the CIPS test indicates that they are stationary. The variables AI and NRR are stationary, i.e. they are integrated of order 0, i.e. I(0). However, when the first differences of all the variables are taken, all the variables are made stationary.

After testing the stationarity of the series, we proceeded with the panel cointegration test, as in Kwilinski et al. [55], presented in Table 5. The second-generation panel Westerlund and Edgerton [109] cointegration test was applied to the analysed variables. As noted in Stevanović et al. [110], Westerlund and Edgerton [109] test provides robust results by addressing serial correlation, heteroskedasticity, cross-sectional dependence, and structural breaks. As for robustness, the Kao and Pedroni cointegration test (the first-generation) was utilised to test the long-run relationship among variables. As shown in Table 5, the results clearly indicate that all the probabilities of the performed tests are less than 0.01. Therefore, we can reject H_0 of no cointegration between the variables and conclude that the panel data are cointegrated. Considering the cointegration tests, as Kwilinski et al. [55] pointed out, it can be concluded that our variables share a long-term equilibrium relationship, moving together over time.

In Table 5, the Breusch-Pagan/Cook-Weisberg test is presented, as well as White's test for heteroscedasticity. Bearing in mind that the p value is less than 0.05 for the Breusch-Pagan/Cook-Weisberg test, it is possible to reject H_0 of constant variance, meaning that there is statistically significant evidence of the existence of heteroskedasticity. Having analysed the results of White's test for heteroscedasticity, it is possible to draw the same conclusion as the previous one. It means that it is possible to reject H_0 of homoscedasticity, considering that the p value is less than 0.05, suggesting that there is statistically significant evidence of heteroscedasticity in the model.

Table 5. Tests for Heteroskedasticity and Cointegration

Kind of test	Statistic	p-value
Heteroskedasticity tests		
Breusch-Pagan / Cook-Weisberg	8.550	0.004
White	170.88	0.000
Cointegration tests		
The second-generation test		
Westerlund	2.344	0.009
The first-generation tests		
Kao	-3.100	0.001
Pedroni test for cointegration		
Modified Phillips-Perron t	6.937	0.000
Phillips-Perron t	-8.271	0.000
Augmented Dickey-Fuller t	-5.518	0.000

Source: Authors' estimation.

Having performed all the tests and checks of the selected variables, a regression analysis was conducted using the GMM model (equations 1 and 2), the FMOLS model (equation 3), the DOLS model (equation 4) and the DCCE-MG model (equation 5), where lnED was taken as a dependent variable. The GMM model was chosen because there are dynamic effects, cross-sectional dependence and heteroscedasticity. Moreover, the model can efficiently solve these problems in the data. On the other hand, when we have mixed stationarity in the variables, it is better to opt for FMOLS and DOLS models. A more comprehensive model for specific features of our data is DCCE-MG, which was employed to check robustness. The full estimation results of the DCCE-MG model are presented in the Appendix Table A1, while the main specification is reported in Table 7.

Table 6 shows that for the GMM model, all the coefficients are statistically significant at the 0.05 level of significance, except for the coefficient next to the variable lnU, which is not statistically significant. The same variable from the previous period has the greatest influence on the lnED variable, i.e. lnED(-1), followed by the next most influential variable lnTR, and, afterwards by the variable lnIS. The variables lnREC, lnNRR and lnAI have a slightly smaller influence on the dependent variable, respectively. As for the results related to FMOLS and DOLS, it is evident that all the coefficients with independent variables are statistically significant at 0.05 level of significance. However, unlike the GMM model, the variable lnU has the greatest influence on the dependent variable lnED. When it comes to the variables lnTR, lnREC, and lnIS, they have a rather large influence on lnED. The variable lnAI has the least influence on lnED, but again this influence is significantly greater than in GMM. Unlike the GMM model, where all the estimated coefficients were positive and statistically significant, in the FMOLS and DOLS models, the variable lnNRR is negative and has a statistically significant effect on lnED.

Table 6. Panel Regression Analysis. The dependent variable is lnED.

Variable	GMM	FMOLS	DOLS
lnED(-1)	0.790***		
lnAI	0.005***	0.099***	0.071***
lnTR	0.199***	0.527***	0.441***
lnNRR	0.010***	-0.183***	-0.165***
lnU	-0.313	1.373***	1.570***
lnREC	0.046**	0.241***	0.143**
lnIS	0.116***	0.202**	0.205**
R^2		0.684	0.660
Adjusted R^2		0.678	0.654
J-statistic (p-value)	22.077 (0.182)		
AR(1)	-1.113 (0.266)		
AR(2)	0.181 (0.856)		

Note: ***, **, * means that p-value is <0.01, <0.05, <0.10, respectively.
Source: Authors' estimation.

Table 6 shows the diagnostic check of the evaluated models. For this purpose, the Sargan/Hansen test and the Arellano and Bond [100] test were used for GMM model. The Sargan/Hansen test (J-statistic) indicates that the instruments are valid, as the p value is greater than 0.1. To put it differently, the J-statistic indicates that the model is correctly evaluated. Arellano and Bond test for autocorrelation (AR(1) and AR(2)) indicates that first- and second-order autocorrelation in the residuals is also not statistically significant. This means that there is no serial correlation in the residuals of the estimated GMM model. The R^2 value for the FMOLS and DOLS models is 68.4% and 66.0%, respectively, indicating that over 60% of the variance in lnED as a dependent variable can be explained through six independent variables. As the estimated coefficients for FMOLS and DOLS are of the same order of magnitude, it can be concluded that the relationship between them is stable and that the estimated means are robust.

To ensure the robustness of estimations, the Dynamic Common Correlated Effects Estimation - Mean Group OLS (DCCE-MG) by Chudik and Pesaran [99] estimator was additionally employed. The main results of DCCE-MG are presented in Table 7.

Table 7. Main results of the DCCE-MG model. The dependent variable is lnED.

Variable	Coef.	Std. Err.	p-value
lnAI	0.011**	0.005	0.036
lnTR	0.060*	0.034	0.082
lnNRR(-1)	-0.072*	0.043	0.097
lnAI_csa	0.027**	0.014	0.050
lnAI(-1)_csa	0.024**	0.011	0.040

lnNRR(-1)_csa	0.094**	0.038	0.014
constant	9.383***	0.773	0.000
Wald χ^2 test	33.00		0.0003

Note: ***, **, * means that p-value is <0.01, <0.05, <0.10, respectively. The suffix _csa is used to denote the cross-sectional average of the preceding variable.
Source: Authors' estimation.

Mean Group OLS (DCCE-MG) by Chudik and Pesaran [106] are presented to ensure the robustness of the results. The model was evaluated based on equation (5). The DCCE-MG model was tested because the data suggested the existence of cross-sectional dependence, heteroskedasticity, mixed stationarity, and cointegration. Table A1 indicates that the Wald χ^2 test is statistically significant because the p value is less than 0.05, implying that the CCE-MG model is significant, that is, there is a joint effect of the independent variables. The variables lnAI, lnAI_csa, lnAI(-1)_csa, as well as lnNRR(-1)_csa have statistically significant coefficients, since the p value is less than 0.05. The variables lnTR and lnNRR(-1) are marginally statistically significant because the p value is less than 0.10. With the DCCE-MG model, it is common that most variables are not statistically significant, as the method is conservative (it corrects errors in a number of ways), that is, it is a very robust model, "strictly" evaluating regressions.

The fact that the variable lnAI is positive and statistically significant at 0.05 level of significance means that a higher level of artificial intelligence (AI) has a positive effect on economic development (ED) as a dependent variable. However, the variables lnAI_csa and lnAI(-1)_csa are also positive and statistically significant at 0.05 level, which implies that the global average AI (common factor) also has a positive effect on ED. Therefore, it means that not only domestic AI but also the "global AI trend" can affect economic development. The variable lnNRR(-1)_csa is also statistically significant at the 0.05 level of significance, implying that the global component of natural resources (NRR) has a significant positive effect on economic development. As the variable lnTR is positive and marginally statistically significant at 0.1 level, it can be concluded that trade (TR) has a positive effect on economic development, at the 10% level of significance, though. As the other variables (U, REC, IS) did not display any statistical significance, we can conclude that they are probably insignificant in the long run in this model, or that their effects disappeared through common components. An additional reason for the insignificance of the other variables may be heterogeneity or the fact that we have a short time period (T=13).

5. Discussions

Based on our results, we can see that the estimated coefficients of the total natural resources rents (NRR) are positive and significant in GMM and DCCE-MG models, yet negative and significant in FMOLS and DOLS models. It means that according to GMM and DCCE-MG models, natural resources increase economic growth, consistent with the findings of Wang and Li [111]. Nevertheless, according to FMOLS and DOLS models, natural resources reduce economic growth, supporting the conclusions reported by Singh et al. [112], Khan et al. [70], and Rahim [47]. Rahim et al. [47] noted that higher natural resources rent inhibited economic growth, whereas Singh et al. [112] showed that there is a negative relationship between NRR and economic growth for the panel. Bakari [12] found limited or nonsignificant impact of natural resources on economic growth, using the Static Gravity Model and GMM estimator. The opposite signs of the NRR coefficients across estimators suggest that the impact of natural resources on economic growth depends on the methodological approach and the time horizon considered. The positive and significant coefficients obtained from the GMM and DCCE-MG models may reflect short-run dynamics and the productive use of resource revenues, particularly in contexts where institutions are relatively effective. In contrast, the negative and significant coefficients from the FMOLS and DOLS estimations, which capture long-run cointegration relationships, point to potential structural constraints associated with resource dependence. Therefore, the divergent findings across models can be interpreted as evidence of heterogeneous short-run and long-run effects of natural resources, as well as differences in how each estimator accounts for endogeneity, cross-sectional dependence, and dynamic adjustments. This nuanced interpretation helps reconcile the mixed empirical evidence in the literature and highlights the importance of institutional quality and time horizon in assessing the growth effects of natural resource rents. Moreover, the contradictory signs of the NRR coefficients across estimators may reflect the dual nature of natural resource dependence discussed in the "resource blessing" [73] and "resource curse" literature [47]. In the short run, natural resource rents may stimulate economic activity through higher export revenues, increased fiscal capacity, and investment expansion, which may explain the positive coefficients obtained in the GMM and DCCE-MG estimations. However, in the long run, excessive dependence on natural resources may weaken economic diversification, increase exposure to external shocks, and reinforce rent-seeking behaviour and institutional inefficiencies. These structural limitations are consistent with the negative coefficients identified by FMOLS and DOLS estimators, which capture long-run equilibrium relationships. Furthermore, Yu [65] argues that the developmental effects of natural resource rents vary across countries and time horizons depending on institutional quality, governance effectiveness, and the broader policy environment. Therefore, the findings suggest that the impact of natural resource rents on economic development depends not only on the time horizon considered, but also on the quality of institutions and the ability of economies to transform resource revenues into productive and innovation-oriented investments.

In Table 6, we can see that the estimated coefficients of renewable energy consumption (REC) in GMM, FMOLS and DOLS are significant, having a

positive impact on economic development (ED). This result coincides with Ali et al. [113] who maintains that REC contributes significantly to long-run economic growth using a panel AMG (Augmented Mean Group) estimator for Asian emerging economies. However, this result does not coincide with Khan et al. [15] for GMM model, Rehman et al [114] for FMOLS model, and Bilan et al. [115] for DOLS model. Khan et al. [15], Rehman et al. [114], and Bilan et al. [115], while using different models, GMM, FMOLS, and DOLS, respectively, indicated that the increase in renewable energy consumption decreases economic growth i.e. REC has a negative relationship with economic growth.
In our case, the estimated coefficient value of trade (TR) is significant and positive in all applied models, which indicates that trade increases economic development (ED). This result is in line with previous results by Khan et al. [15], [99], Shapkova Kocevska and Makrevska Disoska [91], and partially in line with Wang and Li [11], because according to Wang and Li [11], trade openness demonstrates a negative effect in the short run but a positive effect in the long run. Bakari [12] confirmed, using the Static Gravity Model and GMM estimator, the vital roles of trade openness in driving economic growth in the East Asia-Pacific region. Ali and Pasha [92] pointed out that trade openness (TO) had long-run co-integrated relationship with economic growth of Pakistan. Shapkova Kocevska and Makrevska Disoska [91], using OLS panel regressions, showed that trade is statistically significant determinant of economic growth in Central and Eastern Europe, and Western Balkans.

Khan et al. [99] claim that technological innovations stimulate economic growth. The result is similar to our result because after using all applied models it has been demonstrated that the estimated coefficient of Artificial Intelligence (AI) is positive and significant, meaning that higher level of AI has positive impact on economic development (ED) in 24 EU countries. Additionally, similar results to ours are suggested by Wang and Li [11] as well, i.e. artificial intelligence tends to increase economic growth, using NARDL (Nonlinear Autoregressive Distributed Lag) method for China’s economy. Our result coincide with Kalai et al. [41] who suggested that AI has a stimulating effect on economic development, using ARDL model for European countries. Thus, our result is in line with Gonzales [50] who found a positive relationship between AI and economic growth using fixed effects and GMM estimation. Kwilinski et al. [55], using a two-step panel GMM system estimator, found that AI investments have a consistent positive impact on green economic growth.

In our case, the estimated coefficient value of urbanisation (U) is positive and statistically significant in FMOLS and DOLS models, meaning that urbanisation has increased economic development in 24 EU countries. This result does not coincide with Rehman et al. [114] who used FMOLS model and CCR (Canonical Cointegrating Regression) for Romania. Our result coincides with Nguyen and Nguyen [116], because they show that urbanisation positively impacts economic growth in ASEAN countries. Our result is in line with Liu et al. [117], because they indicate that urbanisation has a positive effect on economic growth in Chinese cities, using spatial econometric model. Tripathi and Mahey [118] find a positive link between urbanisation and economic growth in Punjab (India), what is in line with our result. Liang and Yang [119] give “some policy suggestions on how to enhance the positive interaction between urbanisation and economic growth and promote the construction of new green urbanisation”.

Table 6 reveals that the estimated coefficients of industry structure (IS) in GMM, FMOLS and DOLS models are positive and statistically significant, meaning that they have a positive impact on economic development. This result coincides with Elahinia et al. [96], because they point out that the economic growth has a significantly positive association with manufacturing in European economies. Additionally, Haraguchi et al. [97] showed that the manufacturing sector’s value added contributed to world GDP, while Szirmai and Verspagen [98] pointed out to a moderate positive impact of manufacturing on economic growth in developing countries. Ali and Pasha [92] claim that there is bi-variate co-integration between economic growth of Pakistan and manufacturing value added.

6. Conclusion

This study provides robust empirical evidence supporting the multifactorial nature of economic development by integrating technological (AI), environmental (REC, NRR, and U), and structural (trade and industry structure) factors into a comprehensive analytical framework. Employing advanced panel econometric techniques - Generalised Method of Moments (GMM), Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Dynamic Common Correlated Effects Mean Group estimator (DCCE-MG) - the research addresses key data characteristics, including cross-sectional dependence, heterogeneity, mixed stationarity, and cointegration. The results indicate that each of these aspects has a statistically significant impact on GDP per capita in EU-24 countries over the period 2012–2024.

The findings show that artificial intelligence has emerged as a consistently positive and statistically significant driver of economic development across all applied models, underscoring its transformative potential. Trade demonstrates a robust positive relationship with economic development in all estimated models, confirming the vital role of international trade in driving economic growth. This finding aligns with the established trade theory and indicates that the policies which promote trade liberalisation and economic integration significantly contribute to prosperity in EU member states. Urbanisation, renewable energy consumption, and industry structure can positively impact economic growth when analysed through GMM, FMOLS, and DOLS frameworks. Urbanisation fosters agglomeration economies, knowledge spillovers, and improved infrastructure, thereby supporting economic expansion. Renewable energy consumption not only contributes to environmental sustainability but also stimulates economic activity through green technology investments and energy security. The positive coefficient of industry structure emphasises the ongoing significance of manufacturing and industrial value-added in driving economic performance, even in increasingly service-oriented European economies. Conversely, natural resource rents present mixed evidence across estimation techniques: positive in GMM and DCCE-MG, yet negative in FMOLS and DOLS, reflecting complex resource management dynamics. In this context, institutional weaknesses and rent-seeking behaviour can trigger the "resource curse", thus underlining the critical importance of effective governance for translating resource wealth into genuine economic development. These findings confirm the three main hypotheses of the paper and illustrate the model’s usefulness as a strategic tool for achieving the 2030 Agenda for Sustainable Development. The mixed findings regarding natural resource rents further suggest that resource wealth alone does not guarantee long-term economic development without strong institutions and structural diversification policies.

Apart from macroeconomic analysis, the models are also relevant for sector-specific contexts. A potential application can be found in the tourism and hospitality sector, which is particularly affected by digital transformation, natural resource management, and recovery and adaptation dynamics. Tourism experienced significant disruptions during COVID-19, and since that time, it could benefit greatly from AI-based optimisation, renewable energy adoption, and trade-focused recovery strategies. These models provide a comprehensive and flexible resource for developing evidence-based economic policies across various sectors.

This study contributes to the growing body of literature examining the determinants of economic development in the context of technological change and environmental challenges. The inclusion of 24 European countries is particularly important because these economies differ substantially in terms of technological development, energy transition, industrial structure, and overall economic performance. Examining a broader and heterogeneous sample therefore provides more reliable and comprehensive evidence on how AI, trade, renewable energy, urbanisation, natural resource rents, and industry structure affect economic development within the EU framework.

The findings also carry important implications for the European Union's digital and green transition strategies from a policy perspective. The positive impact of artificial intelligence indicates that enhancing AI-related investment, expanding access to venture capital, and fostering innovation ecosystems should remain central priorities within the EU's digital agenda. In parallel, the positive effects of renewable energy consumption and industry structure highlight the need for coordinated policies that simultaneously promote technological advancement and environmental sustainability, in line with the objectives of the European Green Deal [120] and the EU's AI strategy [121]. Overall, the results indicate that digital transformation, green transition, and structural competitiveness should not be pursued as isolated policy domains, but as mutually reinforcing pillars of the long-term resilience and competitiveness of the European economy.

Nevertheless, several limitations should be acknowledged. The relatively short time period (2012-2024) may constrain the identification of long-term relationships, and the heterogeneity across EU countries may mask important country-specific dynamics. In addition, the measurement of artificial intelligence through venture capital (VC) investments in AI-related activities may not fully capture the broader diffusion and real-economy integration of AI technologies. Although VC funding is widely recognised as an important driver of AI innovation, such investments may also reflect short-term capital market conditions rather than long-term technological transformation and the actual integration of AI into the real economy. In addition, VC flows are often concentrated in more innovation-oriented economies and specific industries, which may create measurement bias and reduce cross-country comparability. One additional limitation regarding AI is a relatively short time dimension, resulting from the limited availability of AI-related datasets across selected countries.

Future research could also extend the analysis to other regions, such as the Western Balkans, examine EU countries according to different levels of development, and explore alternative indicators of AI development alongside institutional and governance factors. Further attention should also be devoted to interaction effects between natural resource rents and institutional quality in order to better understand the conditions under which natural resources function either as a source of economic growth or as a structural constraint.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AMG	Augmented Mean Group Estimator
ASEAN	Association of Southeast Asian Nations
CADF	Cross-Sectionally Augmented Dickey–Fuller test
CCR	Canonical Cointegrating Regression
CIPS	Cross-Sectionally Augmented IPS test
DCCE–MG	Dynamic Common Correlated Effects Mean Group estimator
DOLS	Dynamic Ordinary Least Squares
ECOWAS	Economic Community of West African States
ED	Economic Development
EU	European Union
FOLS	Fully Modified Ordinary Least Squares
GCC	Gulf Cooperation Council
GDP	Gross Domestic Product
IS	Industry Structure
MENA	Middle East and North Africa
NARDL	Nonlinear Autoregressive Distributed Lag method
NRR	Natural Resource Rents
REC	Renewable Energy Consumption
OLS	Ordinary Least Squares
TO	Trade Openness
TR	Trade
U	Urbanisation
VC	Venture Capital
VIF	Variance Inflation Factor
WDI	World Development Indicators

Declarations

Author Contributions: Conceptualization, M.M.R. and J.M.; methodology, J.M.; software, J.M.; validation, E.J. and J.M.; formal analysis, J.M. and M.M.R.; investigation, M.M.R.; resources, M.M.R., E.J, M.L.M., and M.P.; data curation, J.M.; writing—original draft preparation, J.M., M.M.R. and E.J.; writing—review and editing, M.L.M., and M.P.; visualization, J.M., M.M.R. and E.J.; supervision, M.L.M., E.J., and M.P.; project administration, M.M.R. and J.M.; funding acquisition, J.M., M.M.R., M.L.M., and M.P. All authors have read and agreed to the published version of the manuscript.

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Appendix A

Table A1. Panel Regression Analysis of DCCE-MG model. Dependent variable is lnED.

Variable	Coef.	Std. Err.	p-value
lnAI	0.011**	0.005	0.036
lnTR	0.060*	0.034	0.082
lnNRR	0.037	0.028	0.188
lnU	-	-	-
lnREC	-0.049	0.059	0.405
lnIS	0.027	0.018	0.130
lnED(-1)	-	-	-
lnAI(-1)	0.005	0.006	0.377
lnTR(-1)	0.023	0.045	0.611
lnNRR(-1)	-0.072*	0.043	0.097
lnU(-1)	-	-	-
lnREC(-1)	-0.025	0.034	0.467
lnIS(-1)	0.026	0.019	0.180
lnED_csa	0.059	0.059	0.317
lnAI_csa	0.027**	0.014	0.050

lnTR_csa	-	-	-
lnNRR_csa	0.012	0.023	0.595
lnU_csa	-	-	-
lnREC_csa	0.026	0.031	0.401
lnIS_csa	-0.047	0.037	0.205
lnED(-1)_csa	-	-	-
lnAI(-1)_csa	0.024**	0.011	0.040
lnTR(-1)_csa	-0.024	0.021	0.261
lnNRR(-1)_csa	0.094**	0.038	0.014
lnU(-1)_csa	-	-	-
lnREC(-1)_csa	-0.022	0.015	0.125
lnIS(-1)_csa	0.016	0.016	0.317
constant	9.383***	0.773	0.000
Wald χ^2 test	33.00		0.0003

Note: ***, **, * means that p-value is <0.01, <0.05, <0.10, respectively. The suffix _csa is used to denote the cross-sectional average of the preceding variable.
Source: Authors' estimation.