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Research Article

AI-Driven Sustainability in EU Nations: A Quantile Regression Analysis of AI Innovations, Human Capital, and Carbon Productivity

AB Ülkelerinde Yapay Zekâ Tabanlı Sürdürülebilirlik: Yapay Zekâ İnovasyonları, İnsan Sermayesi ve Karbon Verimliliği Üzerine Kantil Regresyon Analizi

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Abstract

This study investigates the heterogeneous effects of artificial intelligence (AI) innovations and human capital on carbon productivity in the European Union (EU), focusing on the mediating roles of tertiary education and data literacy. Using an unbalanced panel dataset covering 27 EU countries from 2000 to 2023, the analysis employs quantile regression to capture distributional differences across the conditional distribution of carbon productivity. The results reveal significant non-linearities: AI innovations positively affect carbon productivity at the lower quantile (Q25), but the effect turns negative at higher quantiles (Q75 and Q90), suggesting diminishing returns. Similarly, tertiary education enhances carbon productivity only at lower quantiles, while the interaction term between AI and education becomes strongly positive at the upper end of the distribution, indicating a complementary relationship in high-performing contexts. Conversely, the interaction between AI and data literacy remains negative and significant up to the 75th percentile, implying that digital skills alone may not be sufficient to translate technological progress into environmental efficiency. These findings underscore the importance of tailored green-digital policy strategies that simultaneously foster technological advancement and strengthen human capital foundations, particularly in economies aiming to boost carbon productivity as part of their climate commitments.

***Keywords**: Carbon productivity, Artificial intelligence, Human capital, Quantile regression, European Union, Green transition*

Öz

Bu çalışma, Avrupa Birliği (AB) ülkelerinde yapay zekâ (YZ) inovasyonlarının ve insan sermayesinin karbon verimliliği üzerindeki heterojen etkilerini incelemekte, özellikle yükseköğretim ve veri okuryazarlığı gibi değişkenlerin aracılık rollerine odaklanmaktadır. 2000–2023 dönemini kapsayan, 27 AB ülkesine ait dengesiz panel veri seti kullanılarak yapılan analizde, karbon verimliliğinin koşullu dağılımı boyunca farklılıkları yakalayabilmek amacıyla kantil regresyon yöntemi uygulanmıştır. Elde edilen bulgular, anlamlı doğrusal olmayan ilişkileri ortaya koymaktadır: YZ inovasyonları, düşük kantilde (Q25) karbon verimliliğini olumlu yönde etkilerken, üst kantillerde (Q75 ve Q90) bu etkinin negatife döndüğü görülmektedir; bu durum azalan getiriler olasılığına işaret etmektedir. Benzer şekilde, yükseköğretim yalnızca alt kantillerde karbon verimliliğini artırırken, YZ ve eğitim etkileşim terimi dağılımın üst ucunda anlamlı ve pozitif hale gelmekte, bu da yüksek performanslı bağlamlarda tamamlayıcı bir ilişki olduğunu göstermektedir. Buna karşın, YZ ve veri okuryazarlığı arasındaki etkileşim 75. yüzdelik dilime kadar negatif ve anlamlı kalmakta, bu da dijital becerilerin tek başına teknolojik

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ilerlemenin çevresel verimliliğe dönüşmesi için yeterli olmayabileceğini ima etmektedir. Bu bulgular, özellikle karbon verimliliğini artırmayı hedefleyen ekonomilerde, teknolojik gelişimi desteklerken insan sermayesi temellerini de güçlendirmeye yönelik uyarlanmış yeşil-dijital politika stratejilerinin önemini vurgulamaktadır.

Anahtar Kelimeler: *Karbon verimliliği, Yapay zekâ, İnsan sermayesi, Kantil regresyon, Avrupa Birliği, Yeşil dönüşüm*

1. Introduction

Climate change mitigation has become an imperative for sustainable development, prompting a focus on carbon productivity, the economic output obtained per unit of carbon emissions (European Commission, 2023). Improving carbon productivity is crucial to decoupling growth from greenhouse gas emissions, a goal underscored by global frameworks such as the United Nations Sustainable Development Goals (SDGs). For instance, SDG target 9.4 calls on all countries to upgrade industries for sustainability by increasing resource-use efficiency and adopting clean technologies (European Environment Agency, 2023). Despite incremental decoupling signals in certain economies, the global trajectory of greenhouse gas emissions remains a critical concern. According to the Intergovernmental Panel on Climate Change (IPCC) (2023), total emissions reached approximately 59 gigatons of CO_2-equivalent by 2019, representing a 54% increase since 1990. This upward trend underscores the pressing need for substantial improvements in carbon productivity, particularly if the international community is to meet the climate stabilization targets outlined in the Paris Agreement and the SDGs.

In this context, carbon productivity has gained prominence as a critical metric in environmental economics, offering a composite lens through which climate responsibility and economic performance can be jointly evaluated. It serves as a cornerstone indicator in assessing the extent to which economies are able to generate output while reducing environmental degradation. Public policy has increasingly acknowledged this challenge, as evidenced by the European Green Deal, which commits the European Union to reduce greenhouse gas emissions by at least 55% by 2030 and to achieve climate neutrality by 2050 (European Commission, 2023). These objectives necessitate transformative gains in carbon productivity across EU member states.

Progress toward these targets is already observable. As of 2022, the EU-27 had reduced its emissions to 27% below 1990 levels, while simultaneously sustaining economic growth. Moreover, the EU's share of global emissions declined from nearly 15% in the 1990s to just 6.7%, a reflection of both technological modernization and improved energy efficiency (IPCC, 2023). This decoupling trend, producing more economic value with fewer emissions, underscores the region’s transition toward cleaner technologies and more sustainable practices.

Improving carbon productivity requires both technological innovation and a skilled workforce. While clean technologies offer significant potential to reduce emissions, their effectiveness depends on human capital capable of adopting and utilizing them. Thus, aligning economic growth with climate goals hinges on the synergy between innovation and education, making carbon productivity a strategic lever for sustainable and inclusive development (UNSDG, 2023).

Technological innovation, particularly in digital technologies like artificial intelligence (AI), is increasingly recognized as a potential game-changer for environmental efficiency. Advanced AI applications can optimize energy systems, industrial processes, and supply chains, thereby reducing waste and emissions (Eurostat, 2024). For instance, a recent empirical study in China finds that a 1% increase in AI adoption led to 0.04% decline in CO_2 emission intensity for industrial firms (Eurostat, 2023). AI-driven solutions can improve carbon productivity by enabling more output with the same or lower CO_2 emissions. In line with these benefits, policymakers have encouraged digital innovation as part of climate strategy. The EU’s twin transitions agenda explicitly links the digital transition with the green transition, anticipating that technologies like AI will support decarbonization efforts (OECD, 2023). Indeed, AI is being piloted for applications such as smart grids, predictive maintenance for energy savings, and climate modeling, aligning with calls from the IPCC and others for rapid adoption of clean and smart technologies. AI adoption in the EU, while still at an early stage, is growing rapidly. In 2023 about 8% of EU enterprises had incorporated some form of AI into their business processes. Leading digital economies like Denmark and Finland report the highest adoption rates, whereas several Eastern EU countries remain below 5% (Eurostat, 2024). This uneven uptake points to a digital divide, firms or regions with greater capacity for innovation are quicker to leverage AI for efficiency gains. From an environmental perspective, such disparities could mean that only some countries currently reap AI's carbon-reducing benefits.

Furthermore, the net impact of AI on emissions is unclear. While AI can curb emissions via efficiency, it also increases computing demand, which consumes energy. Some studies (Chishti et al., 2025; Saba et al., 2025; Tsimisaraka et al., 2023) in the literature find that information and communication technology (ICT) usage correlates with lower CO_2 emissions by improving energy efficiency, whereas others caution about rebound effects where digitalization can inadvertently boost energy consumption. Overall, however, a growing body of empirical studies (Khan et al., 2023; Majerník et al., 2023; Zhang et al., 2023) supports the notion that technological innovation, especially when oriented toward clean applications, tends to enhance environmental performance in the long run.

In tandem with technology, human capital is viewed as a critical enabler of sustainable development. Education and skills contribute to environmental outcomes in multiple ways (the United Nations Educational, Scientific and Cultural Organization (UNESCO), 2023). First, a more educated workforce is better equipped to develop, diffuse, and use green technologies, including complex digital tools like AI. Second, higher levels of education tend to elevate environmental awareness and public support for sustainability policies. Empirical evidence by Yao et al. (2020) consistently shows that human capital improvements are associated with lower emissions and greater eco-efficiency. Recently, another studies by Erdem et al. (2023) and Meiwen et al. (2025) have found that increases in average years of schooling and literacy rates lead to reductions in CO_2 emissions over time. Educated societies can more effectively implement energy-saving practices and adapt innovations that reduce the carbon footprint (Hao et al., 2021). In one analysis covering developing economies, human capital had a significant negative impact on CO_2 emissions, indicating that investments in education curb environmental degradation. Similarly, cross-country research by Xin, et al. (2023), finds that key human capital indicators are inversely related to emissions in the long run. These findings align with the theory that knowledge and skills foster both greener technological innovation and more sustainable consumption patterns, thus boosting carbon productivity (Li and Imran, 2025).

Within the EU, however, there are notable gaps in human capital relevant to the digital-green transition. While the Union boasts a generally high level of formal education, digital skills remain uneven. As of 2023, only 55% of EU adults have at least basic digital skills. Countries like the Netherlands and Finland top the list with over 80% of the population digitally literate, whereas others lag below 30% (UNESCO, 2023). This digital skills gap is significant, considering the EU's 2030 target is for 80% of citizens to have basic digital skills. It also mirrors disparities in education quality and access. Such human capital differences may influence how effectively different EU countries can leverage AI and other innovations for carbon productivity gains (Soto, 2024). For instance, a country with a tech-savvy workforce may more readily adopt AI-driven clean technologies (Dechezleprêtre et al., 2013), achieving emissions cuts, whereas countries with skill deficits might struggle to absorb these innovations. Hence, human capital (education, training, data literacy) is likely a complementary factor to technological advancement in driving carbon productivity improvements. The interplay between AI innovations and human capital in the environmental context is, therefore, a critical area of inquiry, with direct relevance for policy initiatives that emphasize both upskilling the labor force and deploying frontier technologies for the green transition.

In addition to the thematic and empirical gaps discussed above, a number of recent studies in the national literature (Akyüz, 2023; Yağlıkara, 2025) have applied quantile regression to analyze the relationships between energy use, emissions, and environmental taxation. These studies typically classify quantile-based research either by methodological focus, such as addressing distributional heterogeneity, or by application area, including energy efficiency or ecological footprint. However, these studies have yet to incorporate emerging digital technologies such as artificial intelligence or to consider the role of human capital in environmental outcomes. Moreover, the interaction effects between AI and education or digital skills have remained largely unexplored in this literature. This study contributes to the expanding quantile regression literature by integrating both AI innovations and human capital as conditional drivers of carbon productivity in a cross-country EU context. By doing so, it addresses both a methodological gap, through distributional estimation, and a thematic gap by linking digitalization and human development with environmental efficiency.

2. Literature Review

A growing body of research explores the links between technological innovation, human capital, and environmental sustainability. For example, ICT-based studies (Alsayegh et al., 2020; Shabir et al., 2023; Liu et al., 2023) find that digital transformation may enhance energy efficiency and reduce CO_2 emissions. Nonetheless, concerns remain regarding rebound effects and increased energy demand (Tsimisaraka et al., 2023), indicating that technological gains may not always translate into environmental benefits.

Despite this expanding literature, the environmental implications of artificial intelligence (AI) remain underexplored. Unlike broader ICT tools, AI operates through distinct mechanisms, such as algorithmic optimization, autonomous systems, and deep learning, which may exert different or more pronounced effects on environmental outcomes, particularly carbon productivity. Although emerging firm-level evidence points to potential benefits, comprehensive analyses at the national or cross-country level are still scarce. This reveals an important research gap concerning the systemic, economy-wide impacts of AI on environmental performance.

Secondly, few studies (Dai et al., 2022; Škare et al., 2024; W. Yao et al., 2024) have explicitly combined human capital and AI as joint determinants of environmental performance. Likewise, some studies (Chen et al., 2025; Husin et al., 2025) have analyzed the impact of education on emissions or energy efficiency. On the other side, technology studies (Cassiman et al., 2010; Habiba et al., 2022) assess how innovation affects carbon outcomes. Yet the interaction between the two, for instance, whether education augments the environmental benefits of AI adoption, is not well understood. This represents an empirical gap that a need for studies that integrate both human capital and technological innovation in explaining variations in carbon productivity. In addition to these content gaps, a methodological gap concerns how the technology and environment relationships are analyzed. Many prior studies, like Akram et al. (2021), employ conventional regression techniques that focus on average effects (e.g. OLS or panel fixed effects estimates of the mean impact on emissions).

Traditional mean-based estimation techniques, such as OLS or fixed effects models, rest on the assumption of homogeneity, implying that the effects of AI innovations or educational attainment on carbon outcomes are consistent across countries and invariant along the distribution of carbon productivity. However, this assumption is often unrealistic. In practice, substantial cross-country heterogeneity exists, and the environmental effectiveness of AI or human capital investments may vary significantly depending on a country's baseline level of carbon productivity and technological maturity. For example, marginal improvements in data literacy may yield substantial gains in low-performing, carbon-intensive economies by unlocking efficiency potential, while producing only limited benefits in high-performing countries already operating near the technological frontier. In such cases, AI deployment may act as a transformative lever in lagging regions but exhibit diminishing returns in more advanced contexts. These distributional dynamics cannot be adequately captured through models that estimate average effects alone. Many studies (Hau et al., 2020 and Hung, 2023) have advocated for analytical techniques that can explore the entire distribution of outcomes. One such approach is quantile regression, which estimates the relationships at different quantiles of the dependent variable's distribution.

Quantile regression offers a robust strategy to address the above heterogeneity. By analyzing conditional quantiles, this method reveals how the influence of predictors can vary across low-performing and high-performing cases by studied by Wu et al. (2025). In the context of this study, employing quantile regression allows us to assess whether the effects of AI innovation and human capital on carbon productivity differ between countries in the lower tail of carbon productivity versus those in the upper tail. This is particularly relevant for the EU, where member states exhibit a range of carbon productivity levels and innovation capacities. Using a distributional approach can uncover patterns that an average regression might mask, for instance, AI adoption might be a game-changer for carbon efficiency in coal-reliant economies (lower quantiles) but have more modest effects in already service-oriented, low-carbon economies (upper quantiles) (Ozkan et al., 2023).

Building on the identified gaps, this study sets out to examine the effects of AI innovations and human capital on carbon productivity across 27 EU countries over the period 2000–2023. The core contribution lies in merging two previously separate strands of inquiry, technological innovation (with a focus on AI adoption) and human capital (education, digital skills), to explain variation in environmental efficiency (carbon productivity). Therefore, this study provides a novel analysis of the "twin transition" in Europe, where digital advancement and green growth intersect. Our introduction of data literacy and education as factors alongside AI is particularly innovative, as it recognizes that technology's impact is mediated by the skill level of the population. We hypothesize that countries investing in both cutting-edge AI and human capital development will achieve the greatest improvements in carbon productivity, aligning with the idea that skilled human resources are necessary to implement and diffuse new technologies effectively.

Methodologically, the study's use of quantile regression represents a significant innovation in examining environmental determinants. This approach allows us to uncover distributional nuances, for example, whether the AI–carbon productivity link is stronger in lower-performing economies, thus offering targeted insights for policymakers. By analyzing effects across quantiles, we move beyond the average relationships and identify if there are threshold effects or nonlinear patterns in how AI and education translate to sustainability outcomes. Such insights can inform differentiated policy strategies, such as lower quantile countries might need foundational investments in human capital before AI can yield environmental benefits, whereas higher quantile countries might focus on frontier innovation to push the envelope of carbon productivity. In summary, this study is motivated by the pressing policy question of how to simultaneously advance digital innovation and human capital to achieve environmental sustainability. We respond by providing an up-to-date empirical investigation set in the EU context, fortified with recent data and global benchmarks. The introduction of AI-related metrics, combined with education and digital skill indicators, into a sustainability framework is a timely contribution given rapid developments in both AI technology and climate policy.

Ultimately, the findings of this study offer evidence on whether accelerating AI adoption and investing in education and data literacy can act as mutually reinforcing drivers of carbon productivity. This evidence aims to support policy initiatives under the European Green Deal and Digital Decade strategies, illustrating how synergistic progress in technology and human capital can help align economic growth with the EU's carbon neutrality ambitions. By filling the identified literature gaps and using an advanced econometric approach, the study provides a comprehensive and nuanced understanding of the AI–human capital-carbon productivity nexus, thereby laying a foundation for more effective, sustainable development policies in Europe and beyond.

3. Data and Methodology

To examine how artificial intelligence (AI) innovations influence carbon productivity in EU countries, with a focus on the mediating roles of education and data literacy. This study utilizes an unbalanced panel dataset covering 27 European Union countries over the period 2000–2023. The primary dependent variable is carbon productivity (LCP), calculated as the ratio of GDP to CO_2 emissions, reflecting the efficiency of economic output relative to environmental pressure. Table 1 provides detailed information on the variables used in the empirical analysis. The dependent variable, carbon productivity (LCP), is calculated as the ratio of gross domestic product (GDP) to CO_2 emissions and serves as a proxy for environmentally efficient economic output. The primary explanatory variable is AI innovations (LAI), measured through AI-related patent applications and R&D expenditures, representing technological advancement toward sustainable production.

Human capital is captured using two distinct but complementary indicators. First, tertiary education attainment (LEDU) reflects formal education levels among the working-age population. Second, data literacy (LD) indicates the share of individuals with above-basic digital skills, representing the capacity to engage with digital and AI-driven technologies. In addition, several control variables are included to account for economic and structural factors influencing carbon productivity. GDP per capita (LGDP) reflects income levels and production intensity. Renewable energy share (LREN) captures the role of cleaner energy sources, while urban population share (LURB) controls population density and urbanization-related environmental pressures.

All variables are measured in consistent units and are sourced from internationally recognized databases, including Eurostat, OECD.AI, WIPO PATENTSCOPE, and the World Bank. Where appropriate, variables have been log-transformed to address skewness and facilitate elasticity-based interpretation within the regression framework.

Table 1. Data Information

Variable Name	Definition	Unit	Source
LCP (Carbon Productivity)	Gross Domestic Product divided by CO_2 emissions	€ per ton CO_2	Eurostat (GDP), Eurostat/EEA
LAI (AI innovations)	Number of AI-related patent applications or AI R&D expenditure	Patents (count) / € million	OECD.AI, WIPO.
LEDU (Tertiary Education)	Share of population (25–34) with tertiary education	% of population	Eurostat
LDL (Data Literacy)	Share of individuals with above-basic digital skills	% of population	Eurostat
LGDP (GDP per capita)	GDP per person (adjusted for inflation)	€ per capita	Eurostat / World Bank
LREN (Renewable energy)	Share of renewables in gross final energy consumption	%	Eurostat
LURB (Urban Population)	Urban population as a share of total population	%	World Bank

To empirically assess the heterogeneous effects of AI innovations and human capital on carbon productivity across EU member states, this study employs a Quantile Regression (QR) approach. QR is particularly suitable for panel data with non-normal error distributions, outliers, and distributional heterogeneity, all of which are common features in sustainability-related macro-panel datasets.

Unlike ordinary least squares (OLS) regression, which estimates the average effect of explanatory variables on the conditional meaning of the dependent variable, QR provides coefficient estimates across different quantiles of the dependent variable's distribution (e.g., 25th, 50th, 75th, and 90th percentiles). This allows us to determine whether the impact of AI innovations and human capital varies for countries with different levels of carbon productivity, offering a more comprehensive understanding of the sustainability transition process. The baseline quantile regression model is specified as:

$$LCP_{it} = \beta_0^{\tau} + \beta_1^{\tau} LAI_{it} + \beta_2^{\tau} LEDU_{it} + \beta_3^{\tau} LDL_{it} + \beta_4^{\tau} LAI * LEDU_{it} + \beta_5^{\tau} LAI * LDL_{it} + X_{it}' \vartheta^{\tau} + \varepsilon_{it}^{\tau}$$

where:

LCP_{it} denotes carbon productivity in country *i* at time *t,*

LAI_{it} represents AI innovations (e.g., AI patents or AI R&D spending),

$LEDU_{it}$ shows tertiary education (proxy for education level),

LDL_{it} denotes data literacy (proxy for digital skills),

$LAI * LEDU_{it}$ captures interaction term capturing whether the effect of AI on carbon productivity depends on education,

$LAI * LDL_{it}$ indicates interaction term capturing AI's dependence on data literacy,

X'_{it} denotes vector of control variables (log GDP per capita, renewable energy share, urban population),

ϑ^{τ} shows coefficient vector for control variables,

ε^{τ}_{it} indicates quantile-specific error term. τ also represents quantile levels (e.g., 0.25, 0.5, 0.75, 0.9). The interaction terms are central to the analysis, as it allows us to test whether the effectiveness of AI innovations in improving carbon productivity depends on the level of human capital in a country.

Table 2 presents the descriptive statistics for the variables used in the empirical analysis, based on 418 country-year observations. The average value of carbon productivity (LCP) is 0.81, with a standard deviation of 0.23, indicating moderate variation across EU countries. The minimum and maximum values suggest significant disparity in environmental efficiency across nations.

The main explanatory variable, AI innovations (LAI), shows a mean of 1.24 and exhibits considerable dispersion, with values ranging from 0 to 4.39, reflecting differences in the intensity of AI adoption. The two human capital indicators, data literacy (LDL) and tertiary education (LEDU), demonstrate relatively low standard deviations, implying that educational and digital skill levels are more homogeneous across the EU sample. Control variables such as LGD) and LURB exhibit expected variation, while renewable LRE shows a wider range from negative values to approximately 1.92. The Jarque-Bera (JB) statistics and associated p-values indicate that all variables deviate significantly from normality, justifying the use of quantile regression, which does not require the assumption of normally distributed residuals. This reinforces the methodological choice of using a distributionally robust estimation approach to capture heterogeneity across the carbon productivity spectrum.

Table 2. Descriptive Statistics

Variable	Obs	Mean	SD	Min.	Max.	JB	Prob.
LCP	418	0.8057	0.234	0.22	1.33	42.18	0.000
LAI	418	1.242138	1.004	0	4.39	24.5	0.000
LGDP	418	4.552834	0.221	3.81	5.08	42.97	0.000
LDL	418	1.705552	0.037	1.59	1.78	10.97	0.000
LEDU	418	2.038065	0.063	1.80	2.21	65.82	0.000
LRE	418	1.248497	0.303	0.46	1.91	34.46	0.000
LURB	418	1.845265	0.911	0	3.78	52.06	0.000

3. Empirical Findings

Before proceeding to the regression analysis, it is essential to assess the direction and strength of the bivariate relationships among the study variables. Figure 1 displays the Kendall rank correlation matrix among the study variables, which serves as a robust tool to examine pairwise monotonic relationships before conducting the regression analysis. Kendall's τ is preferred over Pearson's r in this study due to the presence of non-normal distributions, as previously confirmed by Jarque–Bera tests. The results indicate that carbon productivity (LCP) is positively correlated with GDP per capita, urbanization, and to a lesser extent with AI innovations and education. These findings suggest that countries with higher economic output, urban development, and technological capacity tend to achieve better environmental efficiency.

The correlation between LAI and LEDU is very weak, and similarly, LAI and LDL is negligible, suggesting that AI intensity and human capital levels vary independently across EU countries. This provides strong justification for including interaction terms (e.g., LAI × LEDU, LAI × LDL) in the regression models to detect potential synergistic effects. Additionally, most pairwise correlations fall below |0.50|, which reduces concerns regarding multicollinearity. Nonetheless, LGDP and LDL show a moderate association, which may reflect the role of digital literacy in higher-income economies.

Figure 1. Kendall Correlation Matrix

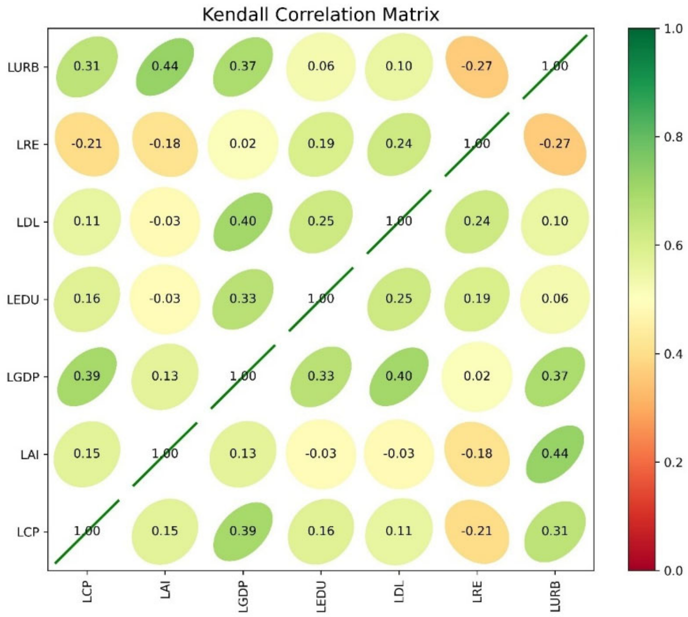


Table 3 presents the results of diagnostic tests assessing cross-sectional dependence and slope heterogeneity across the variables used in the panel analysis. The Breusch–Pagan LM test and Pesaran's Cross-Sectional Dependence (P-CSD) test consistently show statistically significant results for all variables, including (LCP, AI innovations (LAI), and both human capital indicators (LDL and LEDU). This indicates the presence of significant interdependencies among cross-sectional units, likely arising from shared EU policies, technology diffusion, or environmental spillovers. The delta test and adjusted delta test (delta-adj.) also yield statistically significant results for every variable, suggesting that slope coefficients differ across countries. In particular, the adjusted delta values for LEDU, LDL, and LURB are relatively high, reflecting considerable heterogeneity in the marginal effects of education, digital literacy, and urbanization on carbon productivity across the EU.

Table 3. Cross-Sectional Dependence and Slope Heterogeneity Tests

Variables	**Cross-sectional dependence**		**Slope heterogeneity**	
	BP-LM	P-CSD	Delta	delta-adj.
LCP	112.2 (0.000)	55.64 (0.001)	19.08 (0.000)	10.95 (0.000)
LAI	14.97 (0.000)	54.08 (0.000)	15.70 (0.000)	12.35 (0.000)
LGDP	43.12 (0.000)	22.01 (0.001)	29.99 (0.000)	10.88 (0.000)
LDL	58.01 (0.000)	33.02 (0.000)	55.97 (0.000)	28.75 (0.000)
LEDU	73.04 (0.000)	55.64 (0.000)	45.01 (0.000)	19.81 (0.000)
LRE	24.98 (0.000)	66.56 (0.000)	18.91 (0.000)	13.04 (0.000)
LURB	32.44 (0.000)	19.39 (0.000)	21.05 (0.000)	15.58 (0.000)

As shown in Table 4, panel unit root tests were conducted using the second-generation methods of Cross-sectionally Augmented IPS (CIPS) and Cross-sectionally Augmented Dickey-Fuller (CADF), both developed by Pesaran (2007) to account for cross-sectional dependence, previously confirmed in Table 3. The test results indicate that all variables, including carbon productivity (LCP), AI innovations (LAI), GDP per capita (LGDP), education (LEDU), and data literacy (LDL), are non-stationary at the level but become stationary after first differencing, as evidenced by the significant first-difference statistics. These findings further reinforce the choice of quantile-based estimation to investigate heterogeneous effects across the conditional distribution of carbon productivity.

Table 4. Unit Root Test

	CIPS		**CADF**	
Variables	At level	Δ	At level	Δ
LCP	-1.427	-4.967***	-1.638	-3.544***
LAI	-2.182	-5.187***	-1.520	-4.140***
LGDP	-1.518	-5.358***	-1.169	-4.330***
LDL	-1.686	-4.419***	-1.427	-3.189***
LEDU	-0.287	-4.085***	-0.584	-3.067***
LRE	-1.705	-5.570***	-1.174	-3.820***
LURB	-1.506	-5.095***	-0.955	-2.906***

Note: *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Table 5 presents the results of quantile regression estimations conducted at the 25th, 50th, 75th, and 90th percentiles of the conditional distribution of carbon productivity. The results reveal substantial heterogeneity in the impact of AI innovations, human capital, and control variables across different quantiles, confirming the appropriateness of using quantile regression over traditional mean-based models. The coefficient of AI innovations (LAI) is significantly positive at the 25th percentile, indicating that AI contributes to improved carbon productivity in lower-performing countries. However, its effect turns negative and significant at the 75th and 90th percentiles, suggesting potentially diminishing returns or technological inefficiencies at higher productivity levels. This nonlinear pattern highlights the importance of context when assessing AI's environmental role.

GDP per capita (LGDP) maintains a consistently strong and significant positive effect across all quantiles, with the highest impact observed at the median (Q50) reinforcing the notion that economic development enhances carbon efficiency throughout distribution. In contrast, renewable energy share (LRE) exerts a negative and significant effect at all quantiles, implying that the shift toward renewables may not yet yield productivity gains, potentially due to transitional costs or infrastructural limitations. Regarding human capital, tertiary education (LEDU) positively influences carbon productivity only at the lower end ($Q25 = 0.51$, $p < 0.05$) but is negatively associated with productivity at Q75 (-0.90, $p < 0.01$), suggesting that education alone may not translate into environmental efficiency in advanced economies unless coupled with applied digital or technical competencies.

Notably, the interaction term LAI×LEDU becomes significantly positive at higher quantiles (Q75 and Q90), indicating that AI innovations are more effective in enhancing carbon productivity when combined with strong educational systems, especially in high-performing contexts. Conversely, LAI×LDL is consistently negative and significant up to Q75, implying that data literacy alone is not sufficient to maximize the gains from AI technologies and may even dampen productivity in certain cases, possibly due to misalignment between skills and technological deployment.

The negative association between AI innovations and carbon productivity in the upper quantiles (Q75 and Q90) may reflect several structural dynamics. In high-performing countries, AI deployment might be approaching a saturation point, where marginal environmental benefits diminish due to limited scope for further optimization. Additionally, rapid AI development may coincide with rebound effects, such as increased energy demand from AI-driven infrastructure (e.g., data centers), which could offset gains in efficiency. Furthermore, if AI is disproportionately adopted in carbon-intensive sectors (e.g., heavy industry, transport logistics), its net effect on productivity may be less favorable without accompanying green investments or policy safeguards.

Table 5. QR Estimation Results

Series	**Dependent Variable: Carbon Productivity**			
	Q25	Q50	Q75	Q90
C	-1.90*** (0.58)	-2.41*** (0.01)	0.71** (0.01)	-1.72*** (0.01)
LAI	0.63** (0.24)	-0.17 (0.00)	-1.12*** (0.00)	-0.32* (0.00)
LGDP	0.39*** (0.03)	0.57*** (0.06)	0.47*** (0.08)	0.45*** (0.00)
LDL	0.19 (0.00)	0.81 (0.00)	0.20 (0.00)	0.76 (0.00)
LEDU	0.51** (0.00)	-0.14 (0.00)	-0.90** (0.03)	-0.09 (0.00)
LRE	-0.25*** (0.01)	-0.15*** (0.03)	-0.08** (0.04)	-0.14*** (0.05)
LURB	0.05*** (0.01)	0.05*** (0.01)	0.06*** (0.01)	-0.06*** (0.01)
LAI*LEDU	-0.35*** (0.11)	0.04 (0.01)	0.68*** (0.01)	0.34* (0.01)
LAI*LDL	-0.06*** (0.02)	-0.29*** (0.01)	-0.58** (0.11)	-0.15 (0.11)

Note: *, ** and *** indicate significance at 10%, 5% and 1% level, respectively.

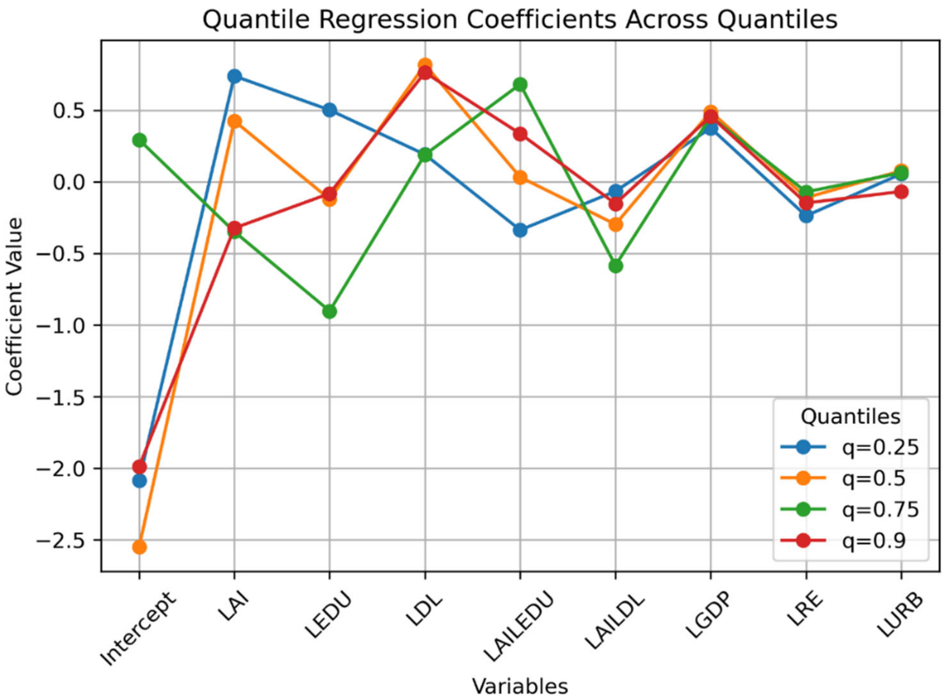
Figure 2 visually illustrates the variation in coefficient estimates for all explanatory variables across the conditional quantiles ($\tau = 0.25, 0.50, 0.75, 0.90$) of carbon productivity, reinforcing the results reported in Table 4. The figure highlights substantial distributional heterogeneity, providing additional empirical support for the use of quantile regression in place of traditional mean-based estimators.

The relationship between AI innovations (LAI) and carbon productivity is highly non-linear across quantiles. While the coefficient is positive at the lower quantiles, suggesting that AI adoption contributes positively to environmental efficiency in lower-performing countries, it becomes increasingly negative at higher quantiles, particularly at $\tau = 0.75$. This pattern implies diminishing or even adverse returns to AI in contexts with high carbon productivity, possibly due to saturation effects or misaligned innovation policies.

Similarly, the interaction term LAI×LEDU demonstrates an upward trajectory across quantiles, becoming strongly positive at the 75th and 90th percentiles. This suggests that the effectiveness of AI innovations is amplified in countries with higher educational attainment, particularly in higher-performing economies. In contrast, the LAI×LDL interaction term shows a consistently negative trend up to the 75th percentile, suggesting that data literacy alone may not be sufficient to unlock the environmental benefits of AI technologies.

GDP per capita (LGDP) remains a strong and stable driver of carbon productivity across all quantiles, as evidenced by its consistently high positive coefficients. On the other hand, renewable energy (LRE) exhibits a relatively uniform negative association, possibly reflecting short-term structural inefficiencies or transition costs in energy systems. Overall, the figure highlights the quantile-dependent nature of the determinants of carbon productivity, underscoring the necessity of tailored sustainability policies based on country-specific conditions and performance levels.

Figure 2. QR Coefficients Across Quantiles of Carbon Productivity



Robustness Checks

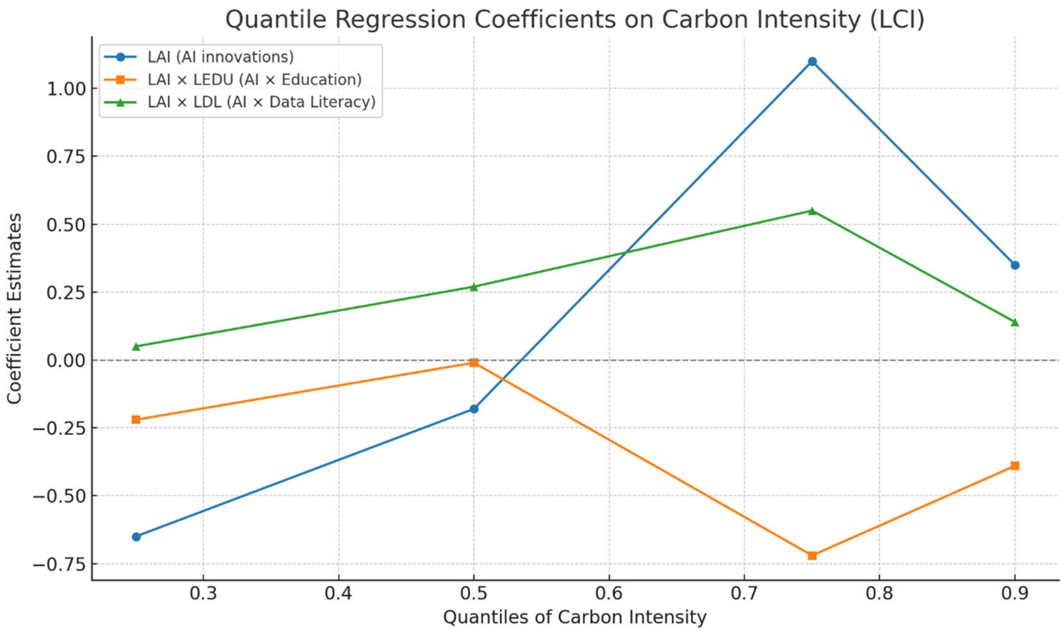
To ensure that our results are not sensitive to the definition of the dependent variable, we re-estimated the quantile regression model using carbon intensity (log of CO_2 emissions per unit of GDP) instead of carbon productivity. The results, presented in Appendix Table A1, reveal that the direction and significance of the key coefficients are consistent with the main findings. Specifically, AI innovations reduce carbon intensity at lower quantiles (Q25), but exhibit diminishing or negative effects at higher quantiles (Q75 and Q90), mirroring the patterns observed in the baseline model. The interaction between AI and education becomes strongly negative at upper quantiles, indicating that higher education levels enhance the decarbonizing impact of AI.

Conversely, the AI–data literacy interaction remains positive and significant up to Q75, suggesting that digital skills alone may be insufficient to reduce carbon intensity. These results confirm that the core conclusions of the study are robust to alternative measures of environmental efficiency.

Figure 3 illustrates the quantile-specific coefficient estimates from the robustness model using carbon intensity as the dependent variable. The impact of AI innovations (LAI) remains negative at lower quantiles (Q25 and Q50), confirming its emission-reducing role in carbon-intensive economies. However, the effect reverses and becomes positive at higher quantiles (Q75 and Q90), suggesting diminishing or even counterproductive returns to AI in high-efficiency countries.

Notably, the interaction term LAI×LEDU is increasingly negative at upper quantiles, supporting the hypothesis that education enhances AI's decarbonizing impact. Conversely, LAI×LDL becomes more positive across the distribution, indicating that digital skills alone may not yield environmental benefits and could exacerbate inefficiencies if unaccompanied by broader institutional or technical capacity.

Figure 3. QR Coefficients on Carbon Intensity



4. Conclusion and Policy Implications

This study investigates the dynamic relationship between artificial intelligence (AI) innovations and carbon productivity across 27 European Union countries from 2000 to 2023, with a specific focus on the mediating roles of education and data literacy as key dimensions of human capital. By employing a quantile regression approach, the analysis captures the distributional heterogeneity of carbon productivity, offering a more nuanced understanding of how technological and human capital factors interact across different performance levels.

The empirical findings reveal that the effects of AI and human capital on carbon productivity are highly context-dependent and non-linear. AI innovations show a significantly positive effect in lower-performing countries (Q25), suggesting that digital technologies can enhance environmental efficiency where baseline productivity is weak. However, at higher quantiles (Q75 and Q90), AI's effect turns negative and statistically significant, implying potential saturation effects, technological inefficiencies, or weak institutional alignment in advanced economies.

Human capital variables also reveal varied effects. While tertiary education (LEDU) boosts carbon productivity at lower quantiles, its standalone impact declines or turns negative in higher-performing economies. Crucially, the interaction between AI and education (LAI×LEDU) becomes strongly positive at Q75 and Q90, underscoring that AI yields the greatest environmental returns when embedded within well-educated systems. Conversely, the AI×data literacy (LAI×LDL) interaction remains negative up to the 75th quantile, suggesting that digital skills alone are not sufficient to harness AI's sustainability potential and may even hinder outcomes if not contextually aligned.

Among the control variables, GDP per capita remains a robust and positive contributor to carbon productivity across all quantiles. In contrast, renewable energy share is negatively associated with carbon productivity, pointing to possible transitional costs, technological bottlenecks, or short-term inefficiencies in clean energy integration. These results collectively highlight the importance of moving beyond average-effect models and adopting distribution-sensitive approaches to better understand how technology and human capital interact in shaping environmental outcomes.

The findings of this study point to the urgent need for differentiated policy strategies in the European Union that take into account the distributional heterogeneity in the relationship between AI innovations, human capital, and carbon productivity. Specifically, the positive effect of AI innovations on carbon productivity at the lower quantiles indicates that countries with relatively weaker carbon performance stand to gain the most from technological adoption. Therefore, policy instruments such as targeted funding, capacity-building programs, and technical assistance should prioritize lower-performing member states to accelerate AI uptake and align it with sustainability objectives. These efforts could be supported through mechanisms like the Digital Europe Programme or Horizon Europe, emphasizing not just digital infrastructure but also environmental integration.

At the same time, the results suggest that AI adoption alone is insufficient to guarantee productivity gains in high-performing countries. In these contexts, where AI's effect turns negative, investments in education, particularly tertiary and technical education, become critical to unlocking the technology's full environmental potential. The strong interaction effect between AI and education at higher quantiles underscores the importance of linking digital innovation with human capital formation. As such, policymakers should expand interdisciplinary curricula that combine AI, environmental science, and engineering, while also fostering university–industry collaboration. This would ensure that the workforce is adequately prepared to apply AI technologies to sustainability challenges.

The consistently negative impact of the interaction between AI and data literacy (LAI×LDL) up to the 75th percentile highlights the limitations of basic digital skill development policies when not matched with sector-specific or applied training. While enhancing digital inclusion remains important, policies must now move beyond foundational literacy to emphasize domain-specific competencies in areas such as green AI applications, energy management, and emissions analytics. In this regard, the EU's Digital Skills and Jobs Coalition could be refined to integrate sustainability modules into digital training programs, thus equipping citizens not just to use technology, but to use it strategically in service of climate goals.

Additionally, the unexpected negative relationship between renewable energy share and carbon productivity suggests that the benefits of clean energy adoption are not immediate and may be hindered by short-term transitional costs, infrastructural inefficiencies, or policy fragmentation. To address this, the EU must complement its ambitious renewable targets with investments in energy storage, grid optimization, and smart energy systems. Furthermore, technical training and institutional reforms are needed to ensure that renewable expansion contributes positively to both environmental and economic performance.

Finally, the use of quantile regression in this study reaffirms that one-size-fits-all climate and digital policies are unlikely to yield optimal results. Policymakers should recognize the asymmetries in AI and human capital effectiveness and design interventions that are sensitive to countries' specific positions along the carbon productivity spectrum. In doing so, the EU can promote a more inclusive and effective green-digital transition, ensuring that environmental benefits of technology and education are fully realized across the region.

Despite its novel contributions, this study has several limitations that merit consideration. First, the use of cross-country panel data may introduce inconsistencies in reporting standards, data availability, and measurement definitions across EU countries, potentially affecting comparability. Second, the measurement of artificial intelligence (AI) innovations is based primarily on AI-related patent applications and R&D spending. While these are widely used proxies, they may not fully capture broader aspects of AI adoption, such as implementation quality, algorithmic maturity, or policy-driven AI deployments. Third, the interaction terms rely on linear specifications, which may oversimplify the complex relationship between AI, human capital, and carbon productivity. Lastly, unobserved institutional or behavioral factors may influence both AI diffusion and environmental performance but remain unaccounted for due to data limitations.

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Araştırma Makalesi

AI-Driven Sustainability in EU Nations: A Quantile Regression Analysis of AI Innovations, Human Capital, and Carbon Productivity

AB Ülkelerinde Yapay Zekâ Tabanlı Sürdürülebilirlik: Yapay Zekâ İnovasyonları, İnsan Sermayesi ve Karbon Verimliliği Üzerine Kantil Regresyon Analizi

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Genişletilmiş Özet

Bu çalışma, Avrupa Birliği (AB) ülkelerinde 2000–2023 dönemini kapsayan bir veri seti üzerinden, yapay zekâ (YZ) inovasyonlarının karbon verimliliği üzerindeki etkilerini analiz etmekte ve bu ilişkide eğitim düzeyi ile veri okuryazarlığının aracılık rollerine odaklanmaktadır. Karbon verimliliği, sürdürülebilir kalkınma ve iklim değişikliğiyle mücadele politikaları açısından kritik bir gösterge olup, bir ekonominin sera gazı emisyonlarını azaltarak ekonomik değer üretme kapasitesini ifade eder. Bu çerçevede, yapay zekâ tabanlı teknolojiler özellikle üretim, enerji yönetimi ve kaynak verimliliği gibi alanlarda optimizasyon sağlayarak karbon yoğunluğunu azaltma potansiyeline sahiptir. Ancak bu potansiyelin gerçeğe dönüşebilmesi için teknolojinin etkin şekilde kullanılması, yani uygun düzeyde insan sermayesi ve uyarlanabilir beceri altyapısı ile desteklenmesi gerekmektedir. Bu bağlamda çalışma, YZ'nin çevresel performansa etkisinin, ülkelerin eğitim düzeyine ve dijital yeterliliğine bağlı olarak farklılaştığını ortaya koymayı amaçlamaktadır.

Çalışmanın temel amacı, YZ inovasyonlarının karbon verimliliğine etkisini, bu etkiyi şekillendiren eğitim (tertiary education) ve dijital beceriler (data literacy) gibi insan sermayesi bileşenleri ile birlikte incelemektir. Araştırmada, 27 AB ülkesine ait dengesiz panel veriler kullanılarak kantil regresyon (quantile regression) yöntemi uygulanmıştır. Bu yöntem, geleneksel ortalama-tabanlı modellerin ötesine geçerek, etkilerin karbon verimliliği dağılımının farklı düzeylerinde nasıl değiştiğini analiz etmeye olanak tanımaktadır. Böylece çalışmanın yöntemi, heterojen politika etkilerini ve ülkelerin çevresel performans seviyelerine göre farklılaşan yapısal dinamikleri ortaya çıkarmayı mümkün kılmaktadır.

Elde edilen bulgular, YZ'nin karbon verimliliği üzerindeki etkisinin kantiller arasında önemli ölçüde farklılaştığını göstermektedir. YZ inovasyonları, düşük performanslı ülkelerde (Q25) karbon verimliliğini anlamlı biçimde artırmakta; buna karşılık, yüksek performanslı ülkelerde (Q75 ve Q90) bu etkinin negatife dönüştüğü gözlemlenmektedir. Bu durum, YZ uygulamalarında azalan getiriler, politik uyumsuzluklar veya verimlilik eşiği etkileri olabileceğine işaret etmektedir. Eğitim (LEDU) değişkeni, karbon verimliliği düşük seviyelerdeyken pozitif katkı sağlamakta; ancak bağımsız etkisi, üst kantillerde anlamlılığını kaybetmektedir. Buna karşın, YZ ve eğitim arasındaki etkileşim terimi, Q75 ve Q90 seviyelerinde anlamlı biçimde pozitif hale gelmekte ve teknolojinin etkisinin ancak gelişmiş eğitim altyapısıyla birlikte anlamlı sonuçlar doğurduğunu göstermektedir.

Buna karşın, YZ ile veri okuryazarlığı (LAI×LDL) arasındaki etkileşim, Q75'e kadar olan tüm kantillerde negatif ve istatistiksel olarak anlamlı çıkmıştır. Bu bulgu, temel dijital becerilerin, YZ tabanlı sürdürülebilirlik katkılarını tek başına gerçekleştirmede yetersiz kalabileceğine işaret etmektedir. Bu bağlamda, dijital becerilerin sektörel uygulama bilgisi ve yeşil dönüşümle uyumlu stratejik entegrasyon ile desteklenmesi gerektiği ortaya konmuştur.

Kontrol değişkenleri kapsamında, kişi başına düşen GSYH (LGDP) tüm kantillerde pozitif ve tutarlı etkiler göstermiş, bu da ekonomik kalkınmanın çevresel verimliliği destekleyici rolünü teyit etmiştir. Ancak, yenilenebilir enerji payı (LRE) değişkeni her bir kantilde negatif ve anlamlı sonuçlar üretmiştir. Bu durum, temiz enerji dönüşümünün henüz verimlilik artışıyla sonuçlanmadığını, altyapısal yetersizlikler, geçiş maliyetleri veya politik uyum eksiklikleri nedeniyle sınırlı etkiler doğurduğunu düşündürmektedir.

Sonuç olarak, bu çalışma teknolojik yeniliklerin çevresel faydaya dönüşmesinin insan sermayesinin niteliğiyle doğrudan ilişkili olduğunu, bu ilişkinin ise ülke düzeyinde farklı performans gösterebildiğini açıkça ortaya koymaktadır. Bulgular, AB ülkelerinde tek tip iklim ve dijitalleşme politikalarının yetersiz kalabileceğini; bunun yerine kantil-temelli, bağlamsal olarak farklılaştırılmış yeşil dijital stratejilere ihtiyaç duyulduğunu göstermektedir. Politika yapıcılar, YZ yatırımlarını, yükseköğretim sistemlerini, uyarlanabilir dijital beceri eğitimlerini ve yeşil altyapı dönüşümlerini entegre eden bütünsel ve esnek politikalar geliştirmelidir. Bu yaklaşım, AB'nin karbon nötr bir ekonomiye geçiş sürecinde verimlilik, eşitlik ve çevresel sürdürülebilirliği aynı anda desteklemesini sağlayacaktır.