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RESEARCH ARTICLE

Artificial Intelligence and Multidimensional Circular Economy Performance in the EU-27: Panel Evidence

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ABSTRACT

Background and Purpose: This study examines the relationship between artificial intelligence (AI) and circular economy (CE) performance in the current European Union (EU-27) countries over the period 2001–2024.
Methods: AI-related capacity and CE performance are measured using multidimensional indices constructed through time-specific heterogeneous factor analysis. The AI index captures national AI-related readiness and adoption capacity rather than the direct intensity of AI deployment. The empirical analysis employs two-way fixed effects with Driscoll-Kraay standard errors and is complemented by lagged AI specifications, Common correlated effects mean group estimation, and Old/New EU heterogeneity analysis.
Results: The results show a positive and statistically significant association with AI-CE performance. This association remains consistent after accounting for cross-sectional dependence, serial correlation, heteroskedasticity, unobserved country heterogeneity, common time shocks, and heterogeneous country responses.
Conclusion: The heterogeneity analysis provides suggestive evidence that the AI-CE association may be stronger in Old EU countries, while the corresponding association in New EU countries is weak and statistically insignificant. These findings suggest that AI is more likely to translate into CE outcomes when supported by mature innovation systems, environmental governance, digital infrastructure, and institutional readiness.

KEYWORDS

Artificial Intelligence; Circular Economy; Time-Specific Heterogeneous Factor Analysis; Driscoll-Kraay; Common Correlated Effects Mean Group

1. INTRODUCTION

The transition from a linear production and consumption model toward a circular economy (CE) has become central to the European Union (EU)'s environmental, industrial, and resource-security agenda (Baldassarre & Carrara, 2025). CE strategies seek to retain the value of products and materials through resource efficiency, reuse, repair, remanufacturing, recycling, and the use of secondary raw materials (Blomsma & Tennant, 2020). The European Commission's CE Action Plan places these objectives within the European Green Deal and extends them across product design, production, consumption, and waste management. Despite this policy commitment, progress remains uneven. In 2024, recycled materials accounted for 12.2% of total material use in the EU, compared with the policy ambition of reaching 23.2% by 2030, while substantial differences remained across member states (European Commission, 2020; Eurostat, 2025). CE performance is inherently multidimensional. Recycling rates alone cannot capture changes in material consumption, waste generation, secondary-resource use, resource productivity, environmental pressures, and circular innovation. The revised EU CE monitoring framework similarly covers production and consumption, waste management, secondary raw materials, competitiveness and innovation, and global sustainability and resilience (Eurostat, 2025). This multidimensional structure motivates the use of a composite measure that reflects several related dimensions of national CE performance rather than relying on a single indicator.

Within this context, artificial intelligence (AI) may support the implementation of CE practices by improving information processing, prediction, automation, and coordination (Handoyo & Sueb, 2026). Circular systems depend on reliable information about products, materials, waste streams, production processes, and supply-chain relationships (Avraamidou et al., 2020). AI-related capabilities may strengthen resource monitoring, waste classification, predictive maintenance, material tracking, reverse logistics, and production planning (Younis & Hamza, 2026). They may also support circular business models by improving lifecycle information and coordinating the recovery and reuse of materials across firms and sectors (Madanaguli et al., 2024). The expected relationship follows a three-stage logic. First, AI-related capacity improves the collection and analysis of information concerning material and resource flows. Second, improved information processing may reduce operational inefficiencies and support waste prevention, resource optimization, recycling, and product-life extension. Third, the conversion of these capabilities into measurable CE outcomes depends on complementary conditions, including digital infrastructure, research capacity, technical skills, data systems, regulation, and organizational absorptive capacity. This argument is consistent with the absorptive-capacity and complementary-assets perspectives, which emphasize that the returns from technological innovation depend on prior knowledge and supporting institutional and organizational resources (Cohen & Levinthal, 1990; Teece, 1986).

In this research, AI is measured using a macroeconomic composite proxy rather than direct measures of AI deployment by individual firms or public institutions. The AI index combines information and communication technology (ICT)-sector gross value added, ICT-sector research and development (R&D) expenditure, internet use by individuals, household internet access, and human resources in science and technology. These indicators capture the digital, innovative, connectivity, and human-capital conditions that support the readiness, diffusion, and potential adoption of AI technologies. The index is therefore interpreted as a measure

of national AI-related readiness and adoption capacity, rather than as a direct measure of the number or intensity of AI systems currently in use. Research on digital technologies and the CE has expanded, although much of the reviewed literature remains conceptual, review-based, firm-level, sector-specific, or focused on particular technological applications. Kristoffersen et al. (2020) connect digital capabilities with circular strategies in manufacturing. Bashynska and Prokopenko (2024) review AI applications in production, supply chains, waste management, and resource recovery, and Madanaguli et al. (2024) examine AI capabilities for circular business-model innovation. These studies provide an important conceptual foundation, but country-level evidence on the relationship between AI and multidimensional CE performance remains limited.

The emerging macro-level literature provides valuable evidence but does not fully address this relationship. Platon et al. (2024) examine AI and eco-investment as determinants of CE development across EU countries using a shorter panel and a different proxy-based measurement framework. Ahmad et al. (2025) construct composite AI-CE indices for 27 EU countries using time-specific heterogeneous factor analysis (TSHFA), but their principal outcome is industrial decarbonization; CE performance is an explanatory variable, while AI is modelled as a moderator. Consequently, limited evidence is available on the direct within-country association between AI-related adoption capacity and multidimensional CE performance over an extended EU panel, particularly after accounting for common shocks, cross-sectional dependence, heterogeneous country responses, and differences between earlier and later EU accession groups. Against this background, the present study examines the relationship between AI and CE performance across the current EU-27 countries over 2001–2024. The balanced panel includes pre-accession observations for countries that joined the EU after 2001. Old EU countries are defined as pre-2004 members included in the current EU-27 sample, while New EU countries comprise states joining through the 2004, 2007, and 2013 enlargement waves. This classification is treated as an accession-cohort comparison rather than a direct measure of institutional quality. The study investigates whether within-country increases in AI-related adoption capacity are associated with stronger CE performance, whether the relationship remains stable under alternative panel specifications, and whether it differs between Old and New EU countries.

This study makes three contributions. First, it constructs and applies multidimensional, time-varying measures of AI-related adoption capacity and CE performance. The AI index captures ICT-sector development, technological research, connectivity, and science-and-technology human capital, while the CE index combines recycling-related patents, consumption footprint, municipal waste generation, packaging- and municipal-waste recycling, circular material use, and resource productivity. Both indices are constructed using time-specific heterogeneous factor analysis (Ahmad et al., 2025), allowing indicator contributions to vary over time. Second, the study provides long-panel evidence on the direct within-country AI-CE association across the current EU-27 over 2001–2024. The empirical framework combines country and year fixed effects with Driscoll–Kraay standard errors and assesses the stability of the results through one- and two-year lagged AI specifications and the Common Correlated Effects Mean Group (CCEMG) estimator, thereby addressing country heterogeneity, common time shocks, cross-sectional dependence, serial correlation, heteroskedasticity, unobserved common factors, and heterogeneous country responses (Driscoll & Kraay, 1998; Pesaran, 2006). Third, the study examines whether the AI-CE association differs between earlier and later EU accession groups, providing indirect evidence on whether differences in innovation systems, digital infrastructure, environmental institutions, regulatory experience, and absorptive capacity condition the strength of the observed association between AI-related capacity and CE performance.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical and empirical literature. Section 3 describes the data, index construction, and econometric methodology. Section 4 analyzes the results. Section 5 concludes with our findings, policy implications, limitations, and avenues for future research.

2. THEORETICAL BACKGROUND AND LITERATURE REVIEW

This study integrates three complementary theoretical perspectives. Industrial ecology provides the foundation for conceptualizing CE performance as the management of interconnected material and energy flows (Saavedra et al., 2018). Innovation diffusion theory describes how a country's overarching technological environment influences the development and adoption of AI technologies (Almaiah et al., 2022). Meanwhile, absorptive capacity theory holds that even when countries possess identical technological resources, their actual success with AI can differ significantly depending on their ability to acquire, understand, and apply new knowledge (Lin & Wu, 2025). Industrial ecology states that reducing the use of raw materials, cutting waste, lowering emissions, and eliminating material losses through improved management of material and energy flows are all necessary to improve resource efficiency (Frosch & Gallopoulos, 1989). This research aligns with CE performance, which highlights resource minimization, extension of the asset lifecycle, and the advancement of circular practices such as maintenance, reuse, repair, remanufacturing, and recycling (Geissdoerfer et al., 2017; Kirchherr et al., 2017). Since CE performance is inherently multidimensional, a single metric is inadequate to measure recycling rates that can coexist with substantial waste generation, primary material dependency, significant consumption footprints, or deficient resource productivity. This research overcomes the limitations of single indicators by deploying a framework that summarizes environmental pressures, waste dynamics, secondary resource circulation, resource productivity, and circular innovation.

Composite measurement nevertheless involves consequential methodological choices. Comparative assessments of CE performance can generate different country rankings because results depend on indicator selection, normalization, weighting, aggregation, and dimensional coverage (Pakuła et al., 2025). The CE index is therefore interpreted as a structured multidimensional representation of relative performance rather than a definitive ranking of national circularity. This interpretation is consistent with industrial ecology while recognizing that any composite index remains conditional on its measurement design. Innovation Diffusion Theory highlights the process within socio-economic systems by explaining perceived advantages, compatibility, communication pathways, and knowledge-acquisition conditions (Orr, 2003). Applied at the national-system level, diffusion also depends on infrastructure, research capability, human capital, and institutional arrangements through which technological knowledge is transmitted and adopted. Castellacci and Natera (2013) similarly show that national innovative capability coevolves with absorptive factors such as infrastructure, international integration, and human capital. These conditions influence an economy's capacity to develop, diffuse, and potentially apply advanced technologies across productive and institutional settings.

Absorptive-capacity theory explains why similar technological resources may yield different outcomes. Cohen and Levinthal (1990) define absorptive capacity as the ability to recognize, assimilate, and apply external knowledge, with an emphasis on prior knowledge and accumulated learning. At the national-system level, it reflects interactions among infrastructure, human capital, research capability, institutions, data systems, and organizational competence (Castellacci & Natera, 2013). Connectivity or technological investment may therefore be insufficient unless economic actors can incorporate AI-related knowledge into production, resource management, environmental monitoring, and CE activities. The accession-cohort comparison is theoretically motivated by possible differences in these absorptive conditions, but it does not constitute a direct test of national absorptive capacity.

The literature identifies four interrelated functions through which AI-related technologies may support CE activities: information processing, prediction, automation, and coordination. These technologies can improve the monitoring of material and waste flows, support predictive maintenance and product-life extension, automate sorting and secondary-material recovery, and strengthen reverse logistics and supply-chain coordination. Such functions may reduce informational and operational barriers to resource efficiency, although they are not separately identified in the country-level analysis. Firm- and sector-level research links digital and AI-related capabilities to data integration, predictive maintenance, waste classification, recycling, reverse logistics, and circular business-model coordination (Madanaguli et al., 2024). These studies identify plausible operational pathways through which advanced digital technologies may support CE activities. Much of the evidence, however, remains organizational, sectoral, conceptual, or review-based and therefore does not establish an economy-wide relationship.

The environmental contribution of digital technologies is not automatically positive. Digital infrastructure and computational activities consume energy and materials, hardware replacement generates electronic waste, and efficiency gains may produce rebound effects when lower costs stimulate additional demand or output (Napoli, 2023). AI-related adoption

capacity is therefore more likely to support CE performance when technological resources are directed toward material efficiency, resource recovery, product-life extension, and environmentally informed decision-making. Digital capacity creates technological possibilities but does not determine how they are governed or applied. Country-level evidence remains limited and heterogeneous. Nham and Bao (2023) identify nonlinear and indicator-dependent relationships between digitalization and CE outcomes, indicating that digital development may facilitate some outcomes at certain levels while producing weaker or adverse associations at others. Their findings reinforce the multidimensional nature of CE performance and imply that linear panel coefficients should be interpreted as average associations rather than universal effects.

Platon et al. (2024) examine AI and eco-investment as explanatory variables for CE development in 27 EU countries over a ten-year period and report a positive relationship. Their study provides direct macro-level evidence but uses a shorter sample and a different proxy-based measurement framework. Ahmad et al. (2025) provide a closely related methodological comparison by constructing AI and CE indices for 27 EU countries over 2000–2023 using time-specific heterogeneous factor analysis. Their principal outcome, however, is industrial decarbonization: CE practices enter as an explanatory factor, while AI moderates the CE–decarbonization relationship. The present study instead treats multidimensional CE performance as the principal outcome and evaluates its conditional within-country association with AI-related adoption capacity across the current EU-27 over 2001–2024.

Overall, emerging evidence is broadly consistent with a positive role for digital and AI-related capacity, but the magnitude and direction of the relationship vary with the circularity indicator, level of digital development, measurement framework, and empirical specification. Organizational studies identify potential mechanisms. Platon et al. (2024) report a positive macro-level association. Nham and Bao (2023) document nonlinear and indicator-dependent patterns. Lin and Wu (2025) demonstrate the sensitivity of comparative CE assessments to measurement design. The empirical proposition developed here is therefore an average conditional association rather than a claim of uniformly positive effects.

Macroeconomic and structural conditions may also be associated with CE performance. R&D reflects the broader national innovation environment, while economic growth, trade openness, industrialization, and urbanization capture differences in demand, production, international integration, productive structure, and settlement patterns. These conditions may create opportunities for resource efficiency while also increasing material pressure. Because their expected associations are theoretically ambiguous and context-dependent, no uniform prior signs are imposed. Aggregate R&D expenditure is retained as a control for the economy-wide innovation environment, consistent with the related empirical literature. European innovation and digital systems exhibit substantial national and regional heterogeneity (Paun et al., 2025). Brodny & Tutak (2024) report higher average enterprise-level digitalization and innovation performance in the Old EU-14 group than in the New EU-13 group, while Mazur-Wierzbicka (2021) identifies marked differences in CE advancement across accession cohorts. These studies establish differences in enabling conditions rather than directly estimating differences in the AI-related capacity-CE slope. Combined with absorptive-capacity theory, however, they motivate the expectation that countries with stronger research, digital, institutional, and implementation capabilities may translate comparable increases in AI-related adoption capacity into stronger CE outcomes. This expectation does not imply that every earlier-accession country outperforms every later-accession country.

For empirical purposes, Old EU countries comprise pre-2004 members of the current EU-27, while New EU countries comprise states that joined in 2004, 2007, and 2013. This fixed classification may proxy for historical and structural differences in transition experience, integration trajectories, industrial structure, innovation systems, and environmental policy development. Because the balanced panel begins in 2001, it includes pre-accession observations for several later entrants. The grouping therefore represents fixed accession cohorts and broader development trajectories rather than the contemporaneous effect of EU membership or membership duration. The analysis identifies differential within-country associations across these historical groups; it does not identify the causal effect of accession, institutional quality, membership duration, or national absorptive capacity. The comparison is consequently interpreted as descriptive accession-cohort heterogeneity.

Taken together, the literature establishes plausible technological mechanisms and provides emerging but non-uniform evidence on the relationship between AI-related adoption capacity and CE performance. Three limitations remain. First, many studies focus on particular technologies, firms, sectors, or individual CE indicators. Second, macro-level studies often use shorter samples, different proxy structures, or models in which CE performance is not the principal outcome. Third, limited evidence examines whether the conditional within-country association differs across fixed EU accession cohorts.

The present study addresses these limitations by applying multidimensional, time-varying AI-related capacity and CE indices to the conditional within-country association across the current EU-27 over 2001–2024. Its contribution lies in treating multidimensional CE performance as the principal outcome and assessing the stability of the estimated association across contemporaneous and lagged specifications, alternative treatments of cross-sectional dependence and unobserved common factors, heterogeneous country responses, and accession-cohort comparisons. These specifications evaluate the timing and stability of the conditional association but do not provide causal identification.

The systemic logic of industrial ecology identifies the material-flow, recovery, and resource-productivity outcomes that information-intensive technologies may support, while innovation-diffusion theory explains how national technological conditions facilitate the spread and potential application of those technologies. Stronger ICT-sector development, technological research, connectivity, and science-and-technology human capital may increase the capacity to generate, process, and diffuse information relevant to material flows, waste streams, maintenance, recovery, and resource allocation. Improved information processing, prediction, automation, and coordination may consequently support product-life extension, secondary-material use, recycling, and resource productivity. The expected relationship remains conditional because the environmental value of technological capacity depends on its application and on complementary skills, investment, governance, and organizational capabilities.

Accordingly, H1: AI is positively associated with CE performance within EU countries. Absorptive-capacity theory further implies that the strength of this association may vary across accession cohorts. Countries with stronger research systems, technological skills, digital infrastructure, administrative capability, and environmental-policy experience may be better positioned to recognize, assimilate, and apply AI-related knowledge to CE activities. Evidence of cohort differences in digitalization, innovation, and CE advancement provides a basis for this directional expectation but does not itself demonstrate a stronger marginal association. The hypothesis is therefore a theoretically derived expectation about average slope heterogeneity rather than a claim of universal superiority or a causal institutional mechanism. Building on this theoretical perspective, H2: The positive within-country association between national AI-related adoption capacity and CE performance is, on average, stronger in Old EU countries than in New EU countries.

3. DATA COLLECTION AND METHODOLOGY

3.1 Variable Definition and Data Collection

This study constructs a balanced panel dataset for 27 EU countries covering the period 2001–2024. The data are obtained from internationally recognized sources, mainly Eurostat and the World Bank World Development Indicators (WDI). The study uses the CE performance index as the dependent variable and the AI index as the main explanatory variable. Gross domestic product (GDP) growth, R&D expenditure, trade openness, industrialization, and urbanization are included as control variables. The CE index is constructed from seven indicators: patents related to recycling and secondary raw materials, consumption footprint, generation of municipal waste per capita, recycling rate of packaging waste, recycling rate of municipal waste, circular material use rate, and resource productivity. The AI index is constructed from five indicators: human resources in science and technology, ICT sector gross value added, internet use by individuals, household internet access, and R&D expenditure of the ICT sector, which is presented in Table 1.

Both CE and AI indices are developed using TSHFA (Ahmad et al., 2025), which allows the contribution of each indicator to vary across time.

Table 1 Variable Source

Symbol	Factors	Sources	Link
CE	Circular economy	Eurostat	https://ec.europa.eu/eurostat
PRSRM	Patent related to recycling and secondary raw materials	Eurostat	https://ec.europa.eu/eurostat
CFT	Consumer footprint	Eurostat	https://ec.europa.eu/eurostat
GMWPC	Generation of municipal waste per capita	Eurostat	https://ec.europa.eu/eurostat
RWPW	Recycling rate of packaging waste Recycling	Eurostat	https://ec.europa.eu/eurostat
RRMW	rate of municipal waste	Eurostat	https://ec.europa.eu/eurostat
CMUR	Circular material use rate	Eurostat	https://ec.europa.eu/eurostat
RP	Resource productivity	Eurostat	https://ec.europa.eu/eurostat
AI	Artificial intelligence	Eurostat	https://ec.europa.eu/eurostat
ICTGAV	ICT in gross added value	Eurostat	https://ec.europa.eu/eurostat
RDEXP	R&D expenditure of ICT sector	Eurostat	https://ec.europa.eu/eurostat
IUBI	Internet use by individuals	Eurostat	https://ec.europa.eu/eurostat
ICTHH	Level of internet access in households	Eurostat	https://ec.europa.eu/eurostat
HRTECH	Human resources in science and technology	Eurostat	https://ec.europa.eu/eurostat
EG	Economic growth	WDI	https://data.worldbank.org/
R&D	Research and development	WDI	https://data.worldbank.org/
GDP	Gross domestic product	WDI	https://data.worldbank.org/
IND	Industrialization	WDI	https://data.worldbank.org/
TO	Trade openness	WDI	https://data.worldbank.org/
URB	Urbanization	WDI	https://data.worldbank.org/

Economic growth, R&D, trade openness, industrialization, and urbanization are measured by annual GDP growth, total R&D expenditures (% of GDP), Trade (% of GDP), industry value added (% of GDP), and Urban population (% of total population), respectively. This study examines whether AI is positively associated with CE performance in the EU region. All acronyms and variable abbreviations are summarized in Table 2.

3.2 Econometric Model

This study examines the relationship between AI and CE performance across the current EU-27 countries over the period 2001–2024. The empirical analysis is guided by two related questions. First, is AI systematically associated with higher CE performance in EU countries? Second, does the relationship differ between Old and New EU countries?

To address these questions, this research applied a panel econometric model with two-way fixed effects and Driscoll-Kraay robust standard errors (FE-DK). EU countries differ systematically in terms of industrial and digital infrastructure, CE policy maturity, innovation capacity, environmental regulation, and institutional quality; based on these, the two-way fixed-effects method is appropriate for this research. By applying this method, year fixed effects account for shared EU-wide shocks, such as macroeconomic disruptions, regulatory cycles, and EU-wide policy changes, while country effects are utilized to capture time-invariant unobserved heterogeneity. Equation (1) presents the baseline model, which attempts to determine the relationship between CE and selected variables.

Table 2 Variable Abbreviation

Serial #	Abbreviation description	Abbreviation
01	Circular economy	CE
02	Artificial intelligence	AI
03	Trade openness	TO
04	Research and development	R&D
05	Industrialization	IND
06	Urbanization	URB
07	Time-specific heterogeneous factor analysis	TSHFA
08	European Union	EU
09	Current 27 EU member states	EU-27
10	Earlier-accession EU member states	Old EU
11	Later-accession EU member states	New EU
12	Common correlated effects mean group estimator	CCEMG
13	Kaiser-Meyer-Olkin measure of sampling adequacy	KMO
14	Cross-Sectional dependence	CSD

$$CE_{it} = \alpha + \beta_1 AI_{it} + \beta_2 GDP_{it} + \beta_3 R\&D_{it} + \beta_4 TO_{it} + \beta_5 IND_{it} + \beta_6 URB_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (1)$$

where CEit, AIit, GDPit, R&Dit, TOit, INDit, and URBit indicate CE, AI, economic growth, R&D, trade openness, industrialization, and urbanization for country i at time t. The terms λ_t and μ_i represent country and year fixed effects, respectively, while ε_{it} is the error term. To ensure robustness, Equation (2) presents further estimates with a lagged AI specification.

$$CE_{it} = \alpha + \beta_1 AI_{i,t-k} + \beta_2 R\&D_{it} + \beta_3 GDP_{it} + \beta_4 TO_{it} + \beta_5 IND_{it} + \beta_6 URB_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

Where $k = 1, 2$. These models examine whether the AI-CE relationship persists when AI enters the model with one-year and two-year lags. This is relevant because the AI-CE association may emerge gradually through improvements in resource monitoring, predictive maintenance, waste-management systems, material-flow optimization, and data-driven environmental governance.

As an additional robustness check, the study applies the CCEMG estimator. CCEMG is appropriate for cross-country panels because it accounts for unobserved common factors and allows slope coefficients to vary across countries.

Finally, the study examines heterogeneity between Old EU and New EU member states. This distinction is theoretically relevant because older EU members generally possess more mature innovation systems, stronger environmental institutions, deeper digital infrastructure, and higher absorptive capacity. The heterogeneity model is specified as follows:

$$CE_{it} = \alpha + \beta_1 AI_{it} + \beta_2 (AI_{it} \times OldEU_i) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Where $OldEU_i$ is an indicator variable equal to one for Old EU member states and zero for New EU member states. Since the Old EU dummy is time-invariant, its direct effect is absorbed by country fixed effects. However, the interaction term remains identifiable because AI varies over time. In this specification, β_1 captures the AI–CE association for New EU countries, while β_2 measures the additional AI effect associated with Old EU countries. A positive and statistically significant interaction term would suggest that the CE-related association of AI is stronger in Old EU economies.

Overall, the econometric strategy combines two-way fixed effects, Driscoll-Kraay robust inference, lagged AI specifications, CCEMG robustness, and Old or New EU heterogeneity analysis. This framework enables the study to examine the AI-CE relationship while accounting for unobserved

country heterogeneity, common time shocks, cross-sectional dependence, serial correlation, heteroskedasticity, and institutional differences across EU member states. The estimates are interpreted as robust conditional associations rather than definitive causal effects.

3.3 Time-Specific Heterogeneous Factor Analysis

This study applies TSHFA to construct the two composite indices used in the empirical analysis: the AI index and the CE performance index. TSHFA is appropriate for panel-based index construction because it allows the relative contribution of each indicator to vary across time, rather than imposing a fixed weighting structure over the full sample period. This feature is particularly relevant for the present study because both AI-related capacity and CE performance are dynamic processes that may evolve across EU countries over the 2001 to 2024 period.

Before index construction, all indicators are normalized using panel-wide min-max normalization. This approach places indicators measured in different units on a common 0–1 scale while preserving comparability across countries and over time. Using common minimum and maximum values for the full panel also ensures that temporal changes in the normalized indicators reflect changes relative to the overall sample rather than year-specific rescaling. Positive indicators are normalized so that higher values represent stronger AI-related capacity or CE performance, while the negatively oriented CE indicators, consumption footprint and municipal waste generation per capita, are reverse-normalized. The normalized indicators are then aggregated through TSHFA to obtain time-varying composite indices of AI and CE performance. Therefore, index stability and statistical adequacy are evaluated using Kaiser-Meyer-Olkin (KMO) and Bartlett's test, and the results are highlighted in a detailed empirical section.

3.4 Cross-Sectional Dependence and Diagnostic Tests

Before estimating the baseline model, this study evaluates whether the panel data are affected by cross-sectional dependence, serial correlation, and heteroskedasticity. This diagnostic step is important because EU economies are closely connected through trade, digital infrastructure, environmental regulation, innovation networks, and common EU policy frameworks. As a result, macroeconomic, technological, or environmental shocks may be correlated across member states. Ignoring such dependence may lead to unreliable statistical inference in conventional fixed-effects models.

To examine cross-sectional dependence, the study applies the Pesaran CD test (Pesaran, 2006), which assesses whether residuals are correlated across countries. The null hypothesis assumes cross-sectional independence, whereas rejecting it indicates that common shocks, spillover effects, or unobserved regional factors may be present in the panel. This test is particularly relevant in the EU context, where member states are economically and institutionally integrated.

The study also tests for serial correlation using the Wooldridge test (Wooldridge, 2010) for autocorrelation in panel data. Serial correlation is relevant in macro-panel settings because both AI and CE performance may follow persistent adjustment patterns over time. In addition, groupwise heteroskedasticity is examined using the modified Wald test for fixed-effects models. This test is appropriate because EU countries differ in economic size, industrial structure, digital capacity, and environmental-policy maturity, which may cause the variance of the error term to differ across countries.

These diagnostic tests guide the selection of the appropriate inference procedure. When cross-sectional dependence, serial correlation, and heteroskedasticity are present, conventional fixed-effects standard errors may produce unreliable inference. Therefore, the preferred specification reports two-way FE-DK, which is robust to heteroskedasticity, autocorrelation, and cross-sectional dependence in the error structure.

3.5 Panel Unit-Root Tests

After evaluating cross-sectional dependence, this study examines the stationarity properties of the variables used in the panel model. This step is important because non-stationary variables may generate misleading regression results if their integration properties are ignored. Since EU countries are economically and institutionally interconnected, conventional first-generation panel unit-root tests may be less reliable when cross-sectional dependence is present. Tests such as Levin-Lin-Chu, Fisher-augmented Dickey-Fuller (ADF), and Fisher-Phillips-Perron (PP) generally assume cross-sectional independence and may therefore provide unreliable inference in the presence of common shocks across countries.

To address this issue, the study employs second-generation panel unit-root tests, namely the Cross-sectional ADF (CADF) test and Pesaran's Cross-sectional Im-Pesaran-Shin (CIPS) test. These tests are appropriate for macro-panel data because they account for cross-sectional dependence by incorporating cross-sectional averages into the testing procedure. This is particularly relevant in the EU context, where CE performance and AI may be influenced by common policy frameworks, technological diffusion, regulatory coordination, and macroeconomic shocks.

The null hypothesis of the CADF and CIPS tests is that the series contains a unit root, while rejection of the null hypothesis indicates stationarity. In this study, the tests are applied at both level and first difference to determine the integration order of the variables before conducting the cointegration assessment, where relevant, and estimating the panel regression models.

3.6 Co-Integration Test

After examining the stationarity properties of the variables, this study applies panel cointegration tests to assess whether a stable long-run association exists among CE performance, AI, and the selected macroeconomic and structural variables. Since the unit-root results indicate that the variables are integrated of order I(0) or I(1), with no evidence of I(2), the cointegration analysis is used as a supplementary test to examine whether the non-stationary components of the model share a long-run equilibrium relationship. Following Pedroni (1999, 2004), this study employs the Pedroni panel cointegration test, which is widely used for heterogeneous panel data and allows for cross-country heterogeneity in the long-run relationship. In addition, Kao (1999) residual-based panel cointegration test is applied as a complementary test under a more restrictive homogeneous framework.

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics

Table 3 presents the descriptive statistics for the variables used in the empirical analysis. The sample consists of 648 country-year observations, covering 27 EU countries over the period 2001–2024. The CE index has a mean value of 0.3689, suggesting that CE performance remains below the upper bound of the normalized scale for much of the sample. The AI index reports a mean value of 0.5234, indicating a higher average normalized value relative to the CE index. Since both indices are bounded between 0 and 1, the minimum and maximum values reflect the normalization procedure and indicate substantial cross-country and temporal variation in the constructed indices.

Among the control variables, GDP growth records a mean value of 2.1015 and a relatively large standard deviation, reflecting considerable macroeconomic variation across countries and years. R&D expenditure has a mean of 1.5300, while trade openness averages 120.8666, consistent with the high degree of external economic integration among EU economies. Industrialization and urbanization report average values of 23.3064 and 72.4428, respectively. The skewness and kurtosis statistics suggest that most variables do not exhibit severe asymmetry, although GDP growth and trade openness show relatively high kurtosis, indicating the presence of extreme observations in some country-year cases.

4.2 Time-Specific Heterogeneous Factor Analysis

This study employs TSHFA to construct two composite indices: the CE performance index and the AI index. TSHFA is suitable for the present panel setting because it allows indicator weights to vary across time rather than imposing a fixed contribution of each variable over the full sample period. This is particularly relevant for EU countries during 2001–2024,

Table 3 Descriptive Statistics

Variable	Mean	Std_Dev	Min	Max	Skewness	Kurtosis
CE	0.3689	0.1857	0	1	0.493	2.783
AI	0.5234	0.2502	0	1	0.024	1.999
GDP	2.1015	3.9221	-14.6423	23.452	-0.148	6.004
R&D	1.53	0.9032	0.2311	3.8922	0.706	2.424
TO	120.8666	60.0986	45.1415	412.1772	1.80	7.760
IND	23.3064	5.7891	9.0098	40.6817	-0.067	2.993
URB	72.4428	12.686	50.78	98.224	0.225	2.085

as both CE performance and AI are multidimensional processes that may evolve with technological progress, environmental policy development, innovation capacity, and structural economic transformation. The CE index is constructed from seven indicators, while the AI index is constructed from five indicators that capture the core dimensions of circularity and AI.

The suitability and statistical adequacy of the index construction are assessed through KMO, Bartlett, scree-plot, and factor-loading diagnostics. Figures 1 and 2 report the KMO test results for the AI and CE indices, respectively.

The overall KMO values are 0.633 for the AI index and 0.718 for the CE index, indicating acceptable sampling adequacy for factor-based index construction. Figures 3 and 4 present the year-wise comparison of the AI and CE indices, showing the temporal distribution and cross-country variation of both indices over the sample period.

Figures 5 and 6 report the year-specific Bartlett test results for the AI and CE indices.

The tests are statistically significant across the sample period, rejecting the null hypothesis that the correlation matrices are identity matrices and supporting the suitability of the selected indicators for factor-based index construction. Figures 7 and 8 present the scree plots, where the first dimension explains 58.9% of the variance in the AI index and 44.2% of the variance in the CE index.

Finally, Figures 9 and 10 show the time-varying factor loadings of the AI and CE indicators, indicating that the relative contribution of individual indicators changes over time.

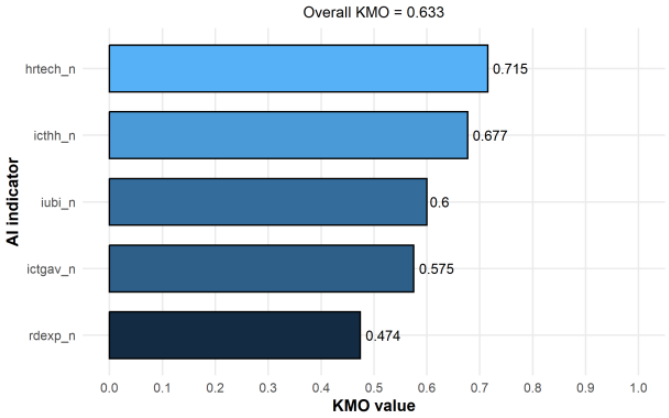


Figure 1 KMO Test Results for the AI Index

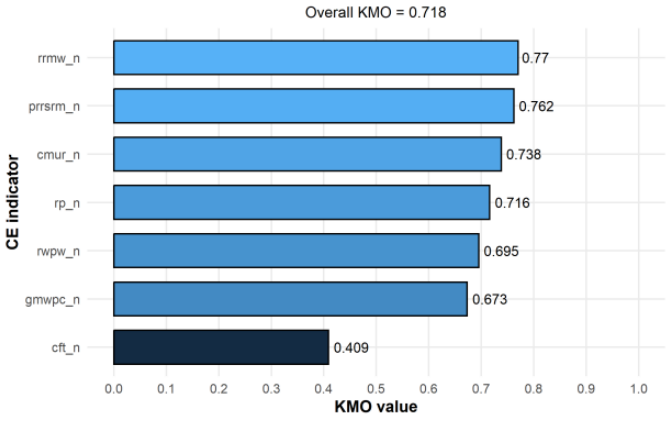


Figure 2 KMO Test Results for the CE Index

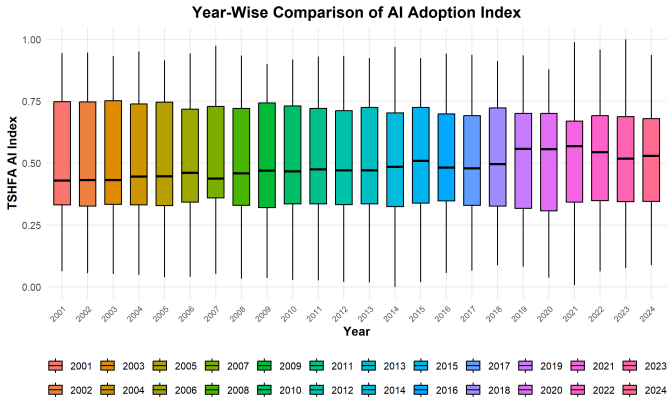


Figure 3 Year-Wise Distribution of the AI Index

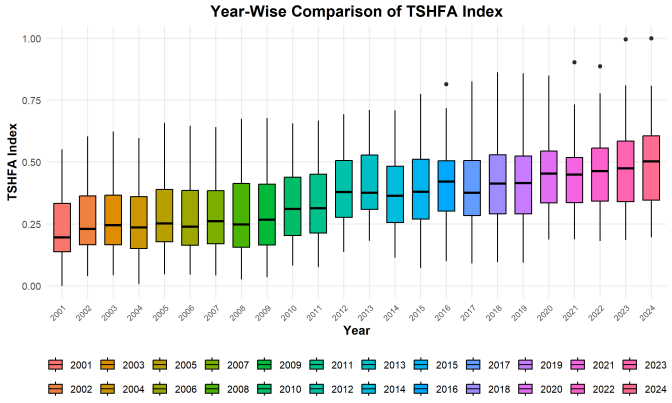


Figure 4 Year-Wise Distribution of the CE Index

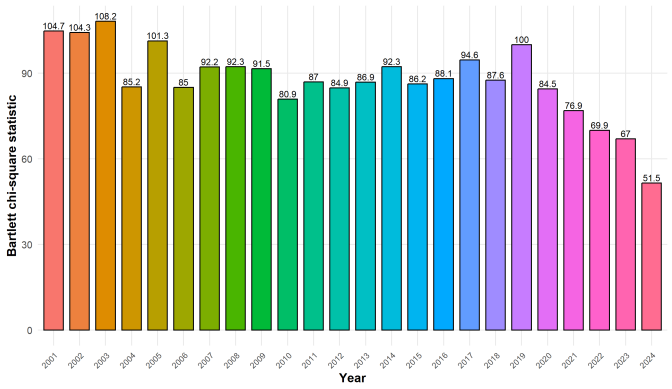


Figure 5 Year-Specific Bartlett Test Results for the AI Index

Overall, these diagnostics support the use of TSHFA-based AI and CE indices in the subsequent panel econometric analysis.

4.3 Panel Unit-Root Tests: CIPS and CADF

After confirming the presence of cross-sectional dependence, this study applies second-generation panel unit-root tests to examine the stationarity properties of the variables. Since first-generation unit-root tests generally assume cross-sectional independence, they may provide unreliable inference in the presence of common shocks across EU countries. Therefore, the study employs the CIPS and CADF tests, which are more appropriate for macro-panel data with cross-sectional dependence.

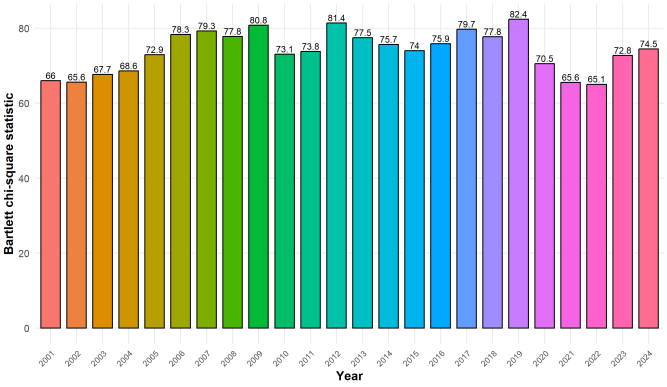


Figure 6 Year-Specific Bartlett Test Results for the CE Index

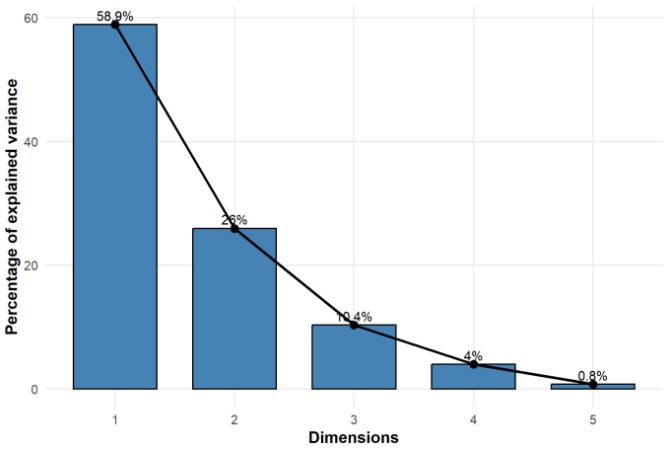


Figure 7 Scree Plot for the AI Index

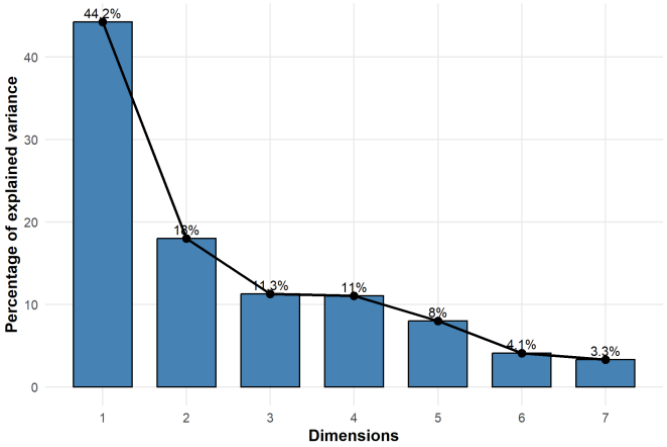


Figure 8 Scree Plot for the CE Index

Table 4 reports the CIPS test statistics and CADF p-values at level and first difference. The results indicate a mixed order of integration. CE, AI, R&D expenditure, trade openness, and industrialization do not show consistent evidence of stationarity at level across the reported deterministic specifications but become stationary after first differencing and are therefore treated as I(1). GDP growth and urbanization exhibit evidence of stationarity at level and are treated as I(0). Overall, no variable is integrated of order I(2), supporting the subsequent cointegration assessment and panel estimation.

4.4 Co-Integration Tests

Table 5 reports the Kao and Pedroni panel cointegration test results. The Kao Modified DF, DF, and ADF statistics are statistically significant at the 1% level, rejecting the null hypothesis of no cointegration. Similarly, the Pedroni modified PP, PP, and ADF statistics are also significant at the 1% level, providing further evidence of a long-run equilibrium relationship among the variables. These results suggest that the relationship between AI, CE performance, and the selected macroeconomic and structural

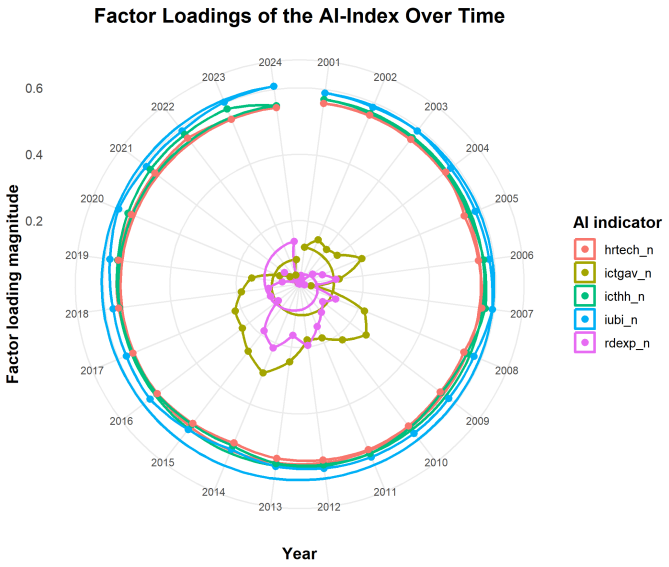


Figure 9 Factor Loadings of the AI Index over Time

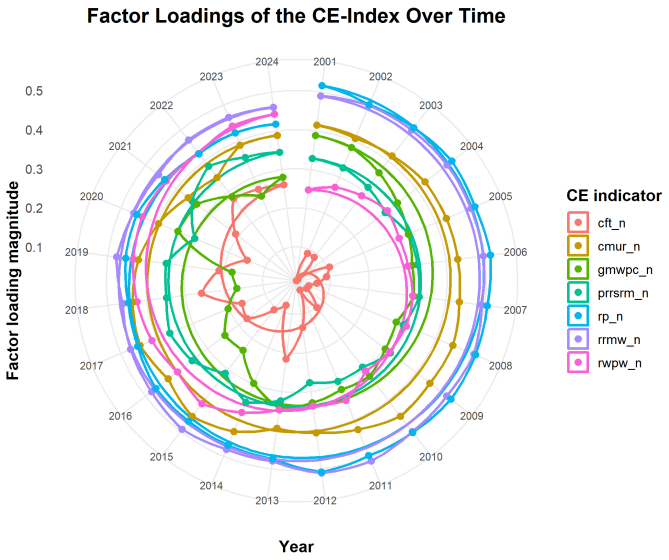


Figure 10 Factor Loadings of the CE Index over Time

controls is consistent with a stable long-run panel association. Therefore, the cointegration evidence supports the subsequent panel estimation strategy.

4.5 Cross-Sectional Dependence and Diagnostic Test

Table 6 presents the cross-sectional dependence and diagnostic test results for the panel dataset.

The Pesaran CD test is statistically significant at the 5% level, indicating the presence of cross-sectional dependence among EU countries. This finding is consistent with the integrated nature of EU economies, where member states are connected through trade, environmental regulation, digital transformation, and common macroeconomic shocks. The Wooldridge test is also statistically significant, indicating first-order serial correlation in the panel. Similarly, the modified Wald test rejects the null hypothesis of groupwise homoskedasticity, suggesting the presence of heteroskedasticity across countries. Taken together, these diagnostic results indicate that conventional fixed-effects standard errors may lead to unreliable inference. Therefore, the preferred baseline estimates are reported using FE-DK, which are robust to cross-sectional dependence, serial correlation, and heteroskedasticity.

Table 4 Panel Unit Root Test CIPS/CADF

Tests	Variables	At level		At first difference		Integration order
		Constant	Trend & Constant	Constant	Trend & Constant	
Panel Unit-Root Test: CIPS (test statistics)	CE	-2.092**	-2.190	-3.424***	-3.606***	I(1)
	AI	-1.149	-2.226	-3.200***	-3.362***	I(1)
	GDP growth	-2.702***	-3.172***	-4.262***	-4.181***	I(0)
	R&D	-2.102**	-2.122	-2.845***	-2.944***	I(1)
	TO	-1.714	-1.726	-2.660***	-3.048***	I(1)
	IND	-2.031*	-2.335	-3.224***	-3.412***	I(1)
	URB	-2.670***	-2.679**	-1.281	-2.225	I(0)
Panel Unit-Root Test: CADF (p-values)	CE	0.035	0.749	0.000	0.000	I(1)
	AI	0.999	0.681	0.000	0.000	I(1)
	GDP growth	0.000	0.000	0.000	0.000	I(0)
	R&D	0.031	0.854	0.000	0.000	I(1)
	TO	0.575	0.999	0.000	0.000	I(1)
	IND	0.068	0.445	0.000	0.000	I(1)
	URB	0.000	0.020	0.994	0.683	I(0)

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

Table 5 Panel Co-Integration Tests: Kao and Pedroni

Test	Statistic	p-value
Kao modified DF	2.9420***	0.0016
Kao DF	3.5033***	0.0002
Kao ADF	4.3672***	0.0000
Pedroni modified PP	2.7964***	0.0026
Pedroni PP	-3.4283***	0.0003
Pedroni ADF	-2.8326***	0.0023

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

Table 6 Cross-Sectional Dependence and Diagnostic Test

Test	Statistic	p-value
Pesaran CD test	-2.469	0.0135
Wooldridge test	139.859	0.0000
Modified Wald test	584.65	0.0000

Source: Author's estimation, STATA 18.0.

4.6 Correlation Matrix and Variance Inflation Factor (VIF) Analysis

Table 7 reports the correlation matrix and variance inflation factor results. The correlation between AI and CE performance is positive at 0.506, indicating a moderate positive bivariate association between the two indices. R&D also shows a strong positive correlation with CE performance, while urbanization is positively correlated with both AI and CE performance. The pairwise correlations among the explanatory variables remain below the conventional threshold of 0.80, suggesting that multicollinearity is unlikely to be a serious concern. This is further supported by the VIF results, where all individual VIF values are below 5, and the mean VIF is 2.01. Overall, the correlation and VIF results provide no evidence of severe multicollinearity, supporting the inclusion of the selected variables in the subsequent regression analysis.

4.7 Baseline Regression Results

Table 8 reports the baseline estimates using two-way FE-DK standard errors. The coefficient of AI is positive and statistically significant in both specifications, indicating a robust positive within-country association between AI and CE performance across EU countries. In the preferred FE-DK specification, the AI coefficient is 0.1255 and significant at the 1% level. Since both the AI and CE indices are normalized between 0 and 1, this implies that a 0.10 increase in the AI index is associated with an approximately 0.0126 increase in the CE performance index, conditional on the control variables, country fixed effects, and year fixed effects. This result suggests that EU countries with rising AI tend to experience stronger CE performance over time.

Among the control variables, R&D expenditure is positive and statistically significant, highlighting the importance of innovation capacity for CE performance. Trade openness has a negative and statistically significant coefficient, suggesting that greater external economic exposure may be associated with resource-use pressures or material-flow intensity. Industrialization is positively significant, indicating that industrial structure remains relevant for CE outcomes in the EU context. The results of other control variables such as GDP and URB are statistically insignificant in the preferred two-way FE-DK. Overall, the baseline results provide robust evidence of a positive conditional relationship between AI and CE performance after accounting for country heterogeneity, common time shocks, and key macroeconomic and structural controls.

4.8 Robustness Analysis

Table 9 presents robustness estimates using lagged AI specifications and the CCEMG estimator.

The baseline FE-DK model reports a positive and statistically significant AI coefficient of 0.1255, supporting a positive conditional association between AI and CE performance. The lagged specifications provide additional support for this relationship. The coefficient of one-year lagged AI is 0.1199 and statistically significant at the 5% level, while the coefficient of two-year lagged AI is 0.1156, also significant at the 5% level. These results indicate that the AI–CE association is not limited to the contemporaneous specification, as AI remains positively associated with CE performance when one-year and two-year lags are introduced. The slightly smaller lagged coefficients indicate that the estimated association remains stable, although its magnitude is somewhat lower in the lagged specifications.

The CCEMG estimator is used as an additional robustness check to account for unobserved common factors, common cross-country shocks, and heterogeneous country-specific responses through the common-correlated-effects structure. The AI coefficient remains positive and statistically significant at 0.0845, suggesting that the main finding is not specific to the two-way fixed-effects specification. Among the controls, R&D expenditure remains positive and significant across all models, while industrialization is also positive and statistically significant. GDP growth and urbanization are statistically insignificant in the CCEMG specification. The change in the sign of trade openness across estimators reflects differences between within-country fixed-effects estimation and heterogeneous common-correlated-effects estimation. Overall, the robustness results provide consistent evidence that AI is positively associated with CE performance across EU countries after introducing lagged AI specifications and accounting for unobserved common factors and heterogeneous country responses.

4.9 Old and New EU Heterogeneity Analysis

Table 10 reports the heterogeneity analysis between Old EU and New EU countries. The subsample estimates show that AI is positively and statistically significantly associated with CE performance in Old EU countries. The coefficient of AI is 0.1229 and significant at the 5% level, indicating that increases in AI are associated with stronger CE performance among older EU member states. In contrast, the AI coefficient for New EU countries is positive but very small and statistically

Table 7 Correlation Matrix and VIF

Variable	CE	AI	GDP	R&D	TO	IND	URB	VIF	1/VIF
CE	1								
AI	0.506	1						3.07	0.326
GDP	-0.23	-0.158	1					1.147	0.872
R&D	0.64	0.662	-0.246	1				2.639	0.379
TO	0.12	0.345	0.072	-0.133	1			1.557	0.642
IND	-0.119	-0.217	0.233	0.015	-0.228	1		1.605	0.622
URB	0.385	0.574	-0.172	0.399	0.232	-0.523	1	2.048	0.488
Mean VIF								2.01	

Table 8 Baseline Regression Results

Variable	Model 1 Two-way FE	Model 2 Two-way FE+DK
AI	0.1255*** (0.0327)	0.1255*** (0.0349)
GDP	-0.0015* (0.0008)	-0.0015 (0.0010)
R&D	0.0531*** (0.0096)	0.0531*** (0.0077)
TO	-0.0006*** (0.0002)	-0.0006*** (0.0001)
IND	0.0045*** (0.0011)	0.0045*** (0.0011)
URB	0.0005 (0.0015)	0.0005 (0.0014)
Country FE	Yes	Yes
Year FE	Yes	Yes
Observations	648	648
Within R^2	0.7498	0.7498

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

insignifican suggesting that the AI–CE association is weak and less precisely estimated among newer EU member states.

The interaction model provides additional evidence of heterogeneity. Since New EU countries are the reference group, the coefficient of AI in the interaction model represents the AI-CE association for New EU countries. This coefficient is positive but statistically insignificant. The interaction term AI × Old EU is positive and statistically significant at the 10% level, providing suggestive evidence that the AI-CE association may be stronger in Old EU countries than in New EU countries. However, because the cross-group difference is only weakly significant, this result should be interpreted cautiously. The post-estimation linear-combination test further shows that the implied AI effect for Old EU countries is 0.2231 and statistically significant at the 1% level. This indicates that, within the pooled interaction framework, AI is positively and significantly associated with CE performance in Old EU economies.

Overall, the heterogeneity results suggest that the AI-CE association may vary across EU accession cohorts. The positive and significant association observed for Old EU countries, together with the weakly significant interaction effect, is consistent with the possibility that stronger innovation systems, environmental governance, digital infrastructure, and institutional capacity facilitate the translation of AI-related capacity into CE performance. However, the formal cross-group evidence remains suggestive rather than conclusive.

5. CONCLUSION

This study examines the relationship between AI and CE performance across the current EU-27 countries over the period 2001–2024. Using TSHFA, the study constructs multidimensional indices for AI and CE performance and estimates their relationship within a panel econometric framework that accounts for country heterogeneity, common time shocks, cross-sectional dependence, serial correlation, heteroskedasticity, and heterogeneous country responses.

The findings provide consistent evidence of a positive conditional association between AI and CE performance. In the preferred two-way FE-DK, the AI coefficient is positive and statistically significant, indicating that increases in AI within countries are associated with stronger CE performance over time. The lagged AI specifications show that this positive association remains present when one-year and two-year lags are introduced, suggesting that the AI-CE relationship is not limited to contemporaneous variation. The CCEMG results further support this finding after accounting for unobserved common factors and heterogeneous country-specific responses.

The results also highlight the role of innovation and structural conditions. R&D expenditure remains positively and significantly associated with CE performance across the main specifications, suggesting that innovation capacity is an important complement to CE development. Industrialization is also positively associated with CE performance, while the role of trade openness varies across estimators. GDP growth and urbanization show weaker and less consistent associations.

The heterogeneity analysis provides suggestive evidence that the AI-CE association may differ across EU accession cohorts. AI-related capacity is positively and significantly associated with CE performance in the Old EU subsample, whereas the corresponding association in the New EU subsample is small and statistically insignificant. In the pooled interaction model, the AI × Old EU coefficient is positive but significant only at the 10% level. Accordingly, the evidence of a stronger AI-CE association in Old EU countries should be interpreted as suggestive rather than conclusive. The post-estimation linear-combination test further shows that the implied AI effect for Old EU countries is positive and statistically significant. These findings suggest that AI may translate more effectively into CE performance in countries with high innovation systems, strong digital infrastructure, greater institutional capacity, and more mature environmental governance.

Overall, the study contributes to the literature by showing that AI is positively associated with CE performance and that this relationship depends on broader institutional and technological conditions. The findings suggest that AI may translate more effectively into CE outcomes when supported by innovation systems, data infrastructure, institutional capacity and mature environmental governance. The results should be interpreted as evidence of robust conditional associations rather than definitive causal effects.

The findings suggest that AI-related digital capacity may serve as a useful complement to CE policy rather than as a standalone technological solution. Policies that strengthen digital infrastructure, innovation systems, environmental data capabilities, technical skills, and institutional readiness may help create conditions under which AI-related capabilities can contribute to resource efficiency, waste monitoring, circular material flows, predictive maintenance, and data-driven environmental governance. The weaker estimated AI-CE association in New EU countries further suggests that targeted capacity-building measures may warrant consideration in countries with less-developed technological and institutional foundations. However, because the present analysis identifies conditional associations rather than causal effects, these policy implications should be interpreted as evidence-informed considerations rather than as estimates of the effects of specific AI-related interventions.

Future research should extend this analysis by examining the causal mechanisms through which AI may influence CE performance. Although this study addresses several panel-data concerns, stronger causal identification could be achieved through policy-shock designs, instrumental-variable approaches, difference-in-differences frameworks, or firm- and sector-level data. Future studies could also disaggregate CE performance into specific channels, such as recycling efficiency, circular material use, waste reduction, resource productivity, industrial symbiosis, and AI-enabled environmental monitoring. In addition, further research may examine whether institutional quality, digital skills, green innovation, environmental regulation, or data-governance capacity mediate or moderate the AI-CE relationship. Such extensions would help clarify not only whether AI is associated with CE performance, but also under what conditions and through which mechanisms AI-related digital transformation translates into measurable CE outcomes.

Table 9 Robustness Analysis

Variable	Baseline FE-DK	FE-DK with AI $_{(t-1)}$	FE-DK with AI $_{(t-2)}$	CCEMG
AI	0.1255*** (0.0349)			0.0845*** (0.0268)
AI t-1		0.1199** (0.0473)		
AI t-2			0.1156** (0.0561)	
GDP	-0.0015 (0.0010)	-0.0013 (0.0010)	-0.0012 (0.0010)	-0.0009 (0.0008)
R&D	0.0531*** (0.0077)	0.0507*** (0.0084)	0.0499*** (0.0090)	0.0518*** (0.0189)
TO	-0.0006*** (0.0001)	-0.0006*** (0.0001)	-0.0006*** (0.0001)	0.0014*** (0.0005)
IND	0.0045*** (0.0011)	0.0042*** (0.0011)	0.0039*** (0.0010)	0.0098*** (0.0031)
URB	0.0005 (0.0014)	-0.0004 (0.0013)	-0.0011 (0.0011)	0.0176 (0.0248)
Country FE	Yes	Yes	Yes	Heterogeneous
Year FE	Yes	Yes	Yes	No
Driscoll-Kraay SE	Yes	Yes	Yes	No
Common correlated effects	No	No	No	Yes
Observations	648	621	594	648
Within R^2	0.7498	0.7370	0.7320	

Note: Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10 Old and New EU Heterogeneity Analysis

Variables	Old EU	New EU	Interaction model
AI	0.1229** (0.0524)	0.0043 (0.0794)	0.0241 (0.0677)
AI × Old EU			0.1991* (0.1023)
Implied Old EU AI effect			0.2231*** (0.0592)
Controls	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Driscoll-Kraay SE	Yes	Yes	Yes
Observations	336	312	648
Within R^2	0.7420	0.8400	0.7533

Notes: Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. New EU is the reference group. The implied AI effect for Old EU countries is calculated as the coefficient on AI plus the coefficient on the interaction term AI × Old EU.

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