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ARTIFICIAL INTELLIGENCE ADOPTION AND ITS INFLUENCE ON CIRCULAR MATERIAL USE: AN EU CROSS-COUNTRY ANALYSIS

Abstract

This research study examines the relationship between Artificial Intelligence (AI) adoption and Circular Material Use Rate across 27 EU member states (2021-2023). Using panel data econometrics and Random Forest machine learning, it analyzes the direct and non-linear effects of AI adoption on circular economy outcomes. Results show no statistically significant direct impact of AI on circular material use rate (CMUSE) when controlling for economic factors. Resource Productivity emerges as the strongest predictor, with GDP per capita playing a crucial moderating role. The Random Forest model explains 48.58% of CMUSE variance. The study provides evidence that AI investments should align with initiatives of increasement of resource efficiency and with economic development policies. The findings emphasize the need for tailored interventions considering technological readiness and economic capacity variations across EU states, contributing to sustainable development policy design.

Keywords: *Artificial Intelligence, Circular Economy, Circular Material Use Rate, European Union, Resource Productivity, Sustainable Development*

JEL classification: *O33, Q55, O52, Q56*

УСВАЈАЊЕ ВЕШТАЧКЕ ИНТЕЛИГЕНЦИЈЕ И ЊЕН УТИЦАЈ НА ЦИРКУЛАРНУ УПОТРЕБУ МАТЕРИЈАЛА: АНАЛИЗА ЗЕМАЉА ЕУ

Апстракт

Овај рад анализира однос вештачке интелигенције и стопе циркуларне употребе материјала у 27 држава ЕУ (2021-2023). Комбинованим приступом економетрије панел података и Random Forest машинског учења, истражени су директни и нелинеарни ефекти вештачке интелигенције на резултате циркуларне економије. Резултати овог истраживања показују да вештачка интелигенција нема статистички значајан утицај на стопу циркуларне употребе материјала

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(CMUSE) при контроли економских фактора. Продуктивност (ефикасност) ресурса је најзначајнији предиктор, док бруто домаћи производ по глави становника има кључну модераторску улогу. Random Forest модел објашњава 48,58% варијансе CMUSE. Ово истраживање је показало да улагања у вештачку интелигенцију треба ускладити са иницијативама за повећање ефикасности ресурса и са политикама привредног развоја, наглашавајући потребу за прилагођеним интервенцијама које узимају у обзир технолошку спремност и економске капацитете држава чланица ЕУ.

Кључне речи: *вештачка интелигенција, циркуларна економија, стопа циркуларне употребе материјала, Европска унија, продуктивност ресурса, одрживи развој*

1. Introduction

Due to resource limitations and environmental devastation, the 21st century has brought forth the dual imperatives of technological transformation and environmental sustainability as defining priorities for modern economies. These challenges are particularly prominent within the European Union (EU), which has positioned itself as a global leader in addressing sustainability concerns, with particular emphasis on resource scarcity and energy efficiency and driving the digitalization of industries. The circular economy (CE) has emerged as a comprehensive framework to mitigate resource depletion and environmental degradation and devastation. At its core, the CE shifts from the dominant, linear "take-make-dispose" model to regenerative systems that prioritize resource efficiency, waste minimization, and material recovery (Geissdoerfer et al., 2017; Kirchherr et al., 2017). By integrating practices such as sustainable product design, reuse, recycling, and recovery, CE aligns economic growth with ecological resilience, representing a cornerstone of the EU's strategy for sustainable development (Ghisellini et al., 2016; MacArthur, 2013).

Simultaneously, artificial intelligence (AI) has evolved as a transformative force in contemporary business, and the speed of its development has forced policymakers, especially in the EU, to adapt fast. AI's capabilities in real-time data processing, predictive analytics, and optimization have enabled innovative solutions across critical sectors, including manufacturing, logistics, and energy management (Jabbour et al., 2022; Lasi et al., 2014). Its potential to enhance CE practices is profound and foundationally transformative. Machine learning algorithms can optimize resource flows (Ghisellini et al., 2016), predictive maintenance systems extend product lifespans (Frank et al., 2019), and advanced robotics improve recycling and waste management (Ramos et al., 2019; Roberts et al., 2022). This synergy between CE and AI creates unprecedented opportunities to address sustainability challenges while fostering economic competitiveness (Wautelet, 2020).

The EU's leadership in CE and digital transformation emphasizes the urgency of understanding how these domains intersect. Policies such as the European Green Deal and the Circular Economy Action Plan (CEAP) set ambitious targets, including increasing the EU's circular material use rate (CMUSE) from 11.7% in 2020 to 25% by 2030 (European Commission, 2020a; Eurostat, 2023). Simultaneously, the Coordinated Plan on AI and the proposed AI Act emphasize ethical and widespread AI adoption to enhance economic and environmental resilience (European Commission, 2020b). These overlapping policy priorities highlight the strategic importance of understanding how AI adoption can bolster CE outcomes, providing a timely context for this research.

However, despite the theoretical promise of AI in advancing CE practices, its empirical impacts remain underexplored, particularly at the macroeconomic level. While case studies and sectoral analyses have demonstrated AI's role in improving resource productivity and enabling circular business models (Popović & Milijić, 2021; Tutore et al., 2024), systematic cross-country evidence is scarce. Popović (2020) notes that research on the implications of Industry 4.0 technologies, including AI, often neglects their potential to achieve sustainable development outcomes like those tied to CE. This gap is particularly pronounced in the EU, where variations in technological readiness, economic development, and industrial structure may influence the effectiveness of AI in promoting CE outcomes. Moreover, the relationship between AI adoption and CMUSE may not be linear, with diminishing returns or threshold effects at higher levels of AI implementation (Platon et al., 2024). Without strong empirical evidence, policymakers and business leaders face uncertainties in leveraging AI to meet CE objectives.

Understanding the interplay between AI adoption and CMUSE is essential for advancing both academic inquiry and policy design. Insights into this relationship can support policymakers in aligning the EU's digital transformation and environmental sustainability agendas. Programs like NextGenerationEU, which allocates €723.8 billion for green and digital transitions, and Horizon Europe, with a €95.5 billion budget for research and innovation, underscore the importance of evidence-based strategies to maximize the impact of these investments (European Commission, 2021c, 2021d). Popović et al. (2023) emphasize that tailored policies accounting for national contexts - such as disparities in technological infrastructure and economic capacity - are crucial for achieving CE targets. For business leaders, identifying how AI can enhance CE practices offers pathways to operational efficiency and competitive advantage.

This research contributes to bridging these gaps by providing macroeconomic-level evidence on the relationship between AI adoption and CMUSE. By focusing on the EU - a global leader in CE and AI adoption - this study contributes to broader discussions on sustainable technological innovation. Moreover, exploring non-linearities and contextual moderating factors enriches the theoretical understanding of how digital and environmental transitions intersect.

The primary goal of this research is to investigate the relationship between AI adoption and CMUSE across EU member states. Four specific objectives support this aim:

1. *Quantifying the causal impact of AI adoption on CMUSE.*
2. *Identifying potential non-linear relationships and threshold effects.*
3. *Analyzing how economic development and technological readiness moderate this relationship.*
4. *Developing evidence-based policy recommendations to enhance CE outcomes through AI adoption.*

The study addresses the following research questions:

1. *How does AI adoption influence circular material use (CMUSE) in EU member states?*

2. *What is the nature of this relationship - linear, non-linear, or threshold-based?*
3. *How do economic development and technological readiness affect this relationship?*

This research employs a mixed-method quantitative approach, integrating panel data econometrics with machine learning techniques to explore the relationship between AI adoption and CMUSE. Using data from 27 EU member states for 2021 and 2023, the analysis captures a pivotal period in the region's digital and circular transitions. Fixed-effects regression models address unobserved heterogeneity among countries and enable causal estimation while controlling for factors such as GDP per capita, resource productivity, and industrial value-added. Additionally, quadratic terms test for potential non-linearities, such as threshold effects or diminishing returns from AI adoption (Platon et al., 2024).

Machine learning complements the econometric analysis by validating results and uncovering complex interactions. Random forest models evaluate variable importance and identify nuanced patterns, providing insights that traditional regression methods might overlook (Breiman, 2001). Partial dependence plots further illustrate the interplay between AI adoption and contextual factors, revealing heterogeneity in impacts across member states. This hybrid approach addresses limitations in prior studies, such as endogeneity concerns and the inability to model non-linear effects (Acerbi et al., 2021).

By integrating econometrics and machine learning, this research advances understanding of the magnitude and nature of AI's influence on CMUSE. The findings align with crucial EU policy frameworks, such as the European Green Deal and CEAP, offering actionable insights for tailoring strategies to enhance the EU's dual transitions in sustainability and digitalization.

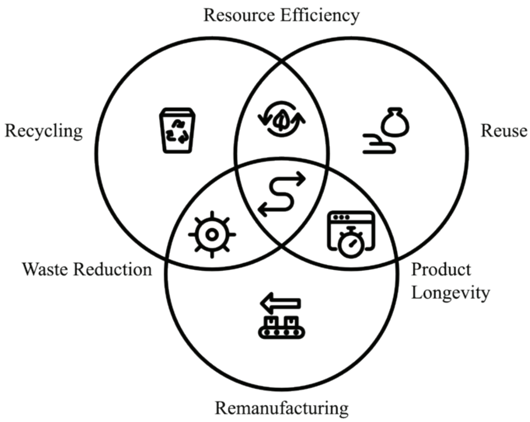
The remainder of this paper is organized to initially review the relevant literature on AI and CE, emphasizing existing gaps and outlining the methodological framework, data sources, and variable selection. Further, it presents empirical findings, including econometric results and machine learning validation, and discusses the implications for policy and practice. Finally, it concludes with key insights and future research directions.

This research makes several contributions to academic literature and policy discussions. First, it provides novel empirical evidence on the relationship between AI adoption and CE outcomes at a macroeconomic level, addressing a critical gap in existing research. Second, it introduces a hybrid methodological approach that combines econometric analysis with machine learning, offering a robust framework for policy analysis. Third, it delivers actionable insights for policymakers and business leaders, aligning with the EU's strategic goals for digital transformation and environmental sustainability. By bridging theoretical understanding and practical application, this research advances the discourse on leveraging AI for sustainable development.

2. Theoretical Background

The integration of circular economy (CE) principles with technological innovation, particularly artificial intelligence (AI), has emerged as a focal point in contemporary discussions on sustainable development. The resource-based view (RBV) and the dynamic capabilities framework provide foundational theories for understanding how organizations can leverage resources and competencies to respond to environmental challenges through resource optimization and technological advancements (Barney, 1991; Teece et al., 1997). Haas et al. (2015) highlight the inefficiencies of the global linear economic model, noting that out of 62 gigatons (Gt) of processed materials, only 4 Gt are recycled annually. This significant disparity underscores the urgent need for a fundamental shift toward circular material flows, aligning with Kirchherr et al. (2017), who emphasize the centrality of CE principles - recycling, reuse, and remanufacturing - in addressing resource scarcity and mitigating environmental degradation and devastation. Figure 1 illustrates the dimensions of the circular economy.

Figure 1: Dimensions of Circular Economy



Source: Author's illustration based on Kirchherr et al. (2017)

Aleksić et al. (2023) extend this perspective by linking sustainable product lifecycle strategies to CE principles. Their study demonstrates that compliance with CE frameworks not only fosters environmental benefits but also enhances profitability. By adopting sustainable design and adhering to CE principles, companies can reduce resource consumption and waste generation, thereby improving their overall economic performance. This integration of theoretical foundations with practical applications emphasizes the imperative for technological innovations, such as AI, to facilitate the transition from linear to circular economic systems.

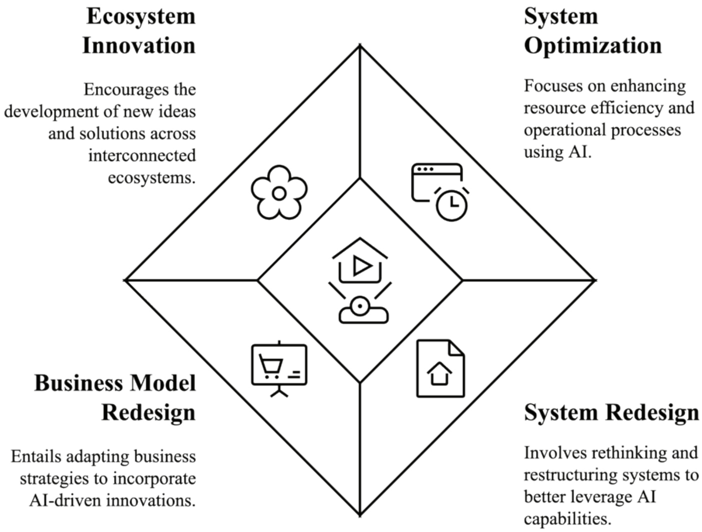
Digital transformation plays a pivotal role in enabling CE practices by leveraging technological solutions to close resource loops, optimize supply chains, and monitor material flows. Technologies such as the Internet of Things (IoT), blockchain, and advanced analytics are instrumental in this domain. Popović et al. (2022) highlight the transformative potential of digital platforms in fostering circular business models like product-as-a-service and extended producer responsibility. These models promote resource efficiency and accountability across value chains, which are essential components in achieving CE goals.

However, the interplay between digital transformation and circularity is complex and often non-linear. Nham and Ha (2022) suggest that while digital technologies offer benefits like precision tracking of materials and enhanced resource recovery, these advantages may diminish beyond a certain threshold. This non-linear dynamic indicates the necessity of aligning technological interventions with strategic policy frameworks to ensure sustained progress toward CE objectives.

In specific industry contexts, Radukić et al. (2023) provide a case study on the textile industry, focusing on H&M's transition toward circularity. Their analysis reveals significant reductions in waste and improvements in operational efficiency through the adoption of digital technologies and CE principles. However, they also highlight the challenges faced by smaller firms and those in resource-limited economies, emphasizing the need for supportive policies and access to technological resources to facilitate broader adoption.

Artificial intelligence has emerged as a transformative enabler in advancing CE practices, offering capabilities in real-time decision-making, predictive analytics, and process optimization. Tutore et al. (2024) propose a four-stage framework for AI integration into CE actions: system optimization, system redesign, business model redesign, and ecosystem innovation. This framework, presented in Figure 2 illustrates the diverse applications of AI, from improving resource efficiency at the operational level to fostering innovation across entire ecosystems.

Figure 2: AI Integration Framework



Source: Author's illustration based on Tutore et al. (2024)

Platon et al. (2024) emphasize the substantial positive impact of AI on CE development, particularly when combined with eco-investments. Their panel regression analysis across 27 EU member states demonstrates that while eco-investment has a greater impact, AI adoption significantly contributes to the advancement of CE outcomes. However, they also note that the extent of this impact varies by industry, organizational maturity, and national policy frameworks.

Similarly, Ghoreishi and Happonen (2020) explore AI's role in sustainable product design, emphasizing how advanced analytics and real-time data can enhance circular manufacturing processes. Their qualitative study suggests that integrating AI techniques in the product design phase leads to improved sustainability and cost savings, although they acknowledge limitations due to the lack of empirical validation.

Despite these promising findings, challenges to AI adoption persist. Cubric (2020) identifies barriers such as data availability, trust issues, and the lack of technical expertise as significant impediments to broader AI implementation. Kelley (2022) further highlights organizational factors, including communication, management support, and ethical considerations, as critical to the successful adoption of AI-driven CE practices.

The European Union (EU) is recognized as a global leader in advancing CE principles, particularly through its focus on circular material use rate (CMUSE). Defined as the percentage of recovered materials reintegrated into the economy, CMUSE serves as a vital indicator of progress toward circularity. According to Eurostat (2023), the EU-wide CMUSE rate was 11.7% in 2020, but this aggregate figure masks significant disparities among member states. Nations with advanced industrial structures and comprehensive policy frameworks, such as Germany and the Netherlands, exhibit higher CMUSE rates, while countries in Eastern and Southern Europe lag due to weaker institutional capacities and technological infrastructure (Popović & Milijić, 2021).

The Circular Economy Action Plan (CEAP), part of the European Green Deal, outlines ambitious goals to increase the CMUSE rate to 25% by 2030 (European Commission, 2020a). Achieving these targets requires innovative approaches, including the adoption of AI, to accelerate the transition to a circular economy. Popović et al. (2023) emphasize that overcoming structural barriers - such as inefficient waste management systems, limited cross-sector collaboration, and uneven technological diffusion - is critical for realizing these objectives.

The application of AI in CE practices has evolved from theoretical explorations to broader implementations across various industries. AI technologies contribute to CE objectives through several mechanisms:

1. Enhanced Waste Sorting: Machine learning and computer vision technologies enable precise identification and separation of waste materials, significantly improving recycling rates. Agrawal et al. (2021) discuss how AI-powered systems can classify materials with greater accuracy and speed than traditional methods, reducing contamination and enhancing the quality of recycled outputs.
2. Predictive Maintenance: AI-driven predictive analytics prolong the lifecycle of products and machinery by identifying potential failures before they occur. Acerbi et al. (2021) emphasize the transformative impact of predictive maintenance on reducing material consumption, particularly in manufacturing and logistics sectors.
3. Supply Chain Optimization: Advanced AI algorithms optimize supply chains by minimizing waste, reducing transportation inefficiencies, and aligning production with demand. Ramos et al. (2018) highlight AI's potential to lower environmental footprints by improving resource allocation and enabling real-time adjustments to supply chain dynamics.

However, scalability challenges persist. While AI has demonstrated significant success at the micro-level (individual firms), its integration at the meso-level (industry networks) and macro-level (regional or national economies) is often limited by regulatory hurdles, infrastructure gaps, and varying levels of technological readiness (Acerbi et al., 2021; Popović et al., 2023). Acerbi et al. (2021) note that the exploitation of AI in circular manufacturing is more advanced at the micro-level compared to meso- and macro-levels, suggesting the need for coordinated efforts to scale AI applications across sectors and regions.

The efficacy of AI in advancing CMUSE is heavily influenced by economic development and institutional quality within EU member states. Wealthier countries with developed institutional frameworks are better positioned to leverage AI technologies for CE objectives. For example:

- Economic Development: Advanced economies like Germany and Sweden have the financial resources and technological infrastructure to invest in AI innovation, enabling more effective implementation of circular strategies (Platon et al., 2024; Popović et al., 2022).
- Institutional Quality: Institutional frameworks that promote collaboration between government, academia, and industry foster environments conducive to AI adoption. Popović et al. (2023) highlight that countries with strong governance and clear CE policies achieve higher rates of technology-driven circularity.

Conversely, less-developed regions face significant barriers, including inadequate infrastructure, limited financial resources, and fragmented policy support. These challenges exacerbate disparities in CMUSE and hinder AI's potential to contribute meaningfully to circular transitions across the EU (Popović & Milijić, 2021). Addressing these disparities requires tailored policy interventions that consider the unique economic and institutional contexts of each member state.

Despite the growing body of literature on AI and CE, notable research gaps persist:

1. Macro-Level Analysis of AI and CMUSE: Current studies predominantly focus on micro-level (firm-specific) or sectoral analyses, neglecting broader macroeconomic dynamics. Popović et al. (2023) underscore the need for cross-country studies that consider the influence of AI adoption on national CMUSE rates, particularly within diverse institutional and economic conditions.
2. Non-Linear Dynamics and Threshold Effects: The relationship between AI adoption and CMUSE may exhibit non-linear characteristics, such as diminishing returns or threshold effects. Nham and Ha (2022) suggest that beyond a certain level of digital technology adoption, the incremental benefits to circularity may decrease, indicating the importance of identifying optimal levels of AI integration.
3. Technological Readiness and Policy Alignment: Platon et al. (2024) emphasize that technological readiness must be complemented by policy frameworks that encourage sustainable AI adoption. Without such alignment, AI's potential to drive CE objectives remains underutilized.

These research gaps inform the methodological choices of this paper. By employing a mixed-method quantitative approach that combines econometric modeling with machine learning validation, this research addresses the limitations of prior studies. Econometric analysis allows for hypothesis testing and estimation of causal relationships, while machine learning techniques capture complex, non-linear interactions and provide robustness checks (Athey & Imbens, 2019). This methodological triangulation enhances the reliability of findings and offers a comprehensive understanding of how AI adoption influences CMUSE across diverse EU contexts.

The scalability of AI applications and their implications for CMUSE across diverse EU contexts are critical considerations. The mixed-method approach enables the examination of both direct effects and detailed interactions between AI adoption and CMUSE. By analyzing data from all 27 EU member states over multiple years, the research captures variations in economic development, technological readiness, and institutional quality. This comprehensive analysis addresses the scalability challenge by identifying patterns and relationships that are generalizable across different contexts.

Moreover, the incorporation of non-linear models and machine learning algorithms allows for the detection of threshold effects and diminishing returns, providing insights into optimal levels of AI adoption for maximizing CMUSE. This is particularly important for policymakers aiming to design interventions that are both effective and efficient.

The literature underscores the transformative potential of AI in advancing CE objectives, particularly in enhancing CMUSE. However, the realization of this potential is contingent upon various factors, including economic development, institutional quality, and strategic policy alignment. The identified research gaps highlight the need for macro-level analyses that consider the complex, non-linear relationships between AI adoption and CMUSE. By addressing these gaps through a robust methodological framework, the present study aims to contribute to both academic discourse and practical policy solutions in promoting sustainable development within the EU.

3. Research Methodology

This research employs a mixed-method quantitative approach to investigate the relationship between Artificial Intelligence (AI) adoption and the Circular Material Use Rate (CMUSE) across the 27 European Union (EU) member states. By integrating traditional econometric techniques with advanced machine learning methods - specifically, panel data econometrics and Random Forest regression – this paper aims to capture both linear and non-linear dynamics in this relationship. This methodological triangulation addresses the limitations of prior studies that often rely solely on linear models or lack robustness checks for complex interactions (Acerbi et al., 2021; Nham & Ha, 2022).

3.1. Data Sources and Sample Selection

The analysis utilizes a balanced panel dataset covering all 27 EU member states over two pivotal years: 2021 and 2023. This period coincides with significant developments in the EU's digital transformation and circular economy initiatives, such as the implementation of the European Green Deal and the Circular Economy Action Plan (CEAP) (European Commission, 2020a). By focusing on this timeframe, the research aims to capture the contemporary dynamics between AI adoption and circular economy outcomes.

The data is sourced from authoritative and harmonized databases to ensure consistency and comparability:

- Eurostat: Provides data on CMUSE, Resource Productivity (RESP), and other circular economy indicators (Eurostat, 2023). Specifically, variables such as Waste Generation per Capita (WASTPC), and Recycling Rates are included.
- European Commission's Surveys: Supplies information on AI adoption rates and digital technology usage, including E-commerce Sales (ECOMS), Cloud Computing Services (CCOMP), and Use of Robotics (ROBOTICS), based on harmonized EU-wide enterprise surveys (European Commission, 2022).
- World Bank and OECD Databases: Provide supplementary macroeconomic data

such as GDP per Capita (GDPpc), Unemployment Rates (UNEMP), Industrial Value Added (INDVA), and Renewable Energy Consumption (RENWENG) for validation and robustness checks.

By concentrating on the EU context, this paper controls for overarching policy frameworks and institutional settings, thereby addressing scalability challenges and ensuring that variations in the data are attributable to differences in national characteristics rather than global disparities (Popović et al., 2023).

3.2. Variables and Operationalization

Dependent Variable: Circular Material Use Rate (CMUSE) measures the share of material recycled and reintroduced into the economy, thus reducing the need for extracting primary raw materials. It is defined as the ratio of the circular use of materials to the overall material use and is expressed as a percentage (%) (Eurostat, 2023).

Independent Variable: Artificial Intelligence Adoption Rate (AI) represented by the percentage of enterprises employing at least one AI technology, such as machine learning, natural language processing, or computer vision. This data is collected from enterprises with 10 or more employees across various sectors, excluding agriculture, forestry, fishing, and mining (European Commission, 2022).

Control Variables: To account for country-specific characteristics and potential confounding factors, several control variables are included:

- E-commerce Sales (ECOMS): Percentage of enterprises making sales via e-commerce, serving as a proxy for digital infrastructure and technological readiness (Eurostat, 2023).
- Cloud Computing Services (CCOMP): Percentage of enterprises buying cloud computing services used over the Internet, indicating the level of digital adoption (European Commission, 2022).
- Resource Productivity (RESP): Calculated as gross domestic product (GDP) divided by domestic material consumption (DMC), expressed in Euro per kilogram. This variable captures the efficiency of resource utilization (Eurostat, 2023).
- Industrial Value Added (INDVA): Represents the contribution of the industrial sector (including construction) to GDP, expressed as a percentage (%). It controls for structural economic differences across countries (World Bank, 2024).
- GDP per Capita (GDPpc): Gross domestic product divided by midyear population, measured in current U.S. dollars. It accounts for the level of economic development (World Bank, 2024).
- Renewable Energy Consumption (RENWENG): The share of renewable energy in total final energy consumption, expressed as a percentage (%). It reflects a country's commitment to sustainable energy practices (World Bank, 2024).

Additional Variables: For robustness checks and supplementary analysis, the analysis includes:

- Waste Generation per Capita (WASTPC): Total waste generated per capita, including major mineral wastes, measured in kilograms (Eurostat, 2023).
- Recycling Rates: Including Recycling Rate of Municipal Waste (RECMWASTE) and Recycling Rate of Electronic Waste (RECREW), expressed as percentages (%), to assess specific aspects of waste management efficiency.

- Unemployment Rate (UNEMP): The share of the labor force without work but available for and seeking employment, expressed as a percentage (%). This variable controls for labor market conditions (World Bank, 2024).

All variables are carefully operationalized and standardized where appropriate to ensure comparability and to mitigate issues of scale and multicollinearity (Wooldridge, 2010).

3.3. Data Preparation and Processing

Data was collected from the respective databases to ensure the most recent and relevant information was utilized. Each variable is matched with its short definition, date of collection, and source link for transparency and reproducibility.

The dataset is structured as a balanced panel (Croissant & Millo, 2008), with countries as individual units and years as time periods. This structure allows us to control for unobserved heterogeneity and capture both cross-sectional and temporal variations.

Variable Transformation:

- Standardization: Continuous variables are standardized using z-scores to address scale differences and facilitate the interpretation of coefficients.
- Log Transformation: The natural logarithm of GDP per capita (lgdp) is taken to linearize the relationship and reduce heteroscedasticity.
- Composite Indices: Where appropriate, composite indices are created using Principal Component Analysis (PCA) to capture underlying constructs such as technological readiness or environmental sustainability.

All analyses are conducted using R statistical software version 4.4.0 (R Core Team, 2024), utilizing packages such as plm for panel data econometrics (Croissant & Millo, 2008), randomForest for machine learning models (Liaw & Wiener, 2002), and ggplot2 for data visualization (Wickham, 2016). The use of R ensures transparency, reproducibility, and accessibility.

3.4. Empirical Strategy and Model Specifications

Stage 1 - Linear Panel Data Analysis: The analysis begins with a fixed-effects panel regression model to estimate the direct relationship between AI adoption and CMUSE:

$$\mathrm{CMUSE\_std}_{it} = \beta_1 \mathrm{AI\_std}_{it} + \beta_2 \mathrm{lgdp}_{it} + \beta_3 \mathrm{RESP\_std}_{it} + \beta_4 \mathrm{INDVA\_std}_{it} + \alpha_i + \epsilon_i \qquad (1)$$

- $\mathrm{CMUSE\_std}_{it}$: Standardized Circular Material Use Rate for country iii at time ttt.
- $\mathrm{AI\_std}_{it}$: Standardized AI Adoption Rate.
- Lgdp_{it}: Natural logarithm of GDP per capita.
- $\mathrm{RESP\_std}_{it}$: Standardized Resource Productivity.
- $\mathrm{INDVA\_std}_{it}$: Standardized Industrial Value Added.
- α_i\alpha_iαi: Country-specific fixed effects.
- ϵ_{it}: Error term.

The fixed-effects model accounts for unobserved heterogeneity by allowing each country to have its own intercept, thus controlling for time-invariant characteristics (Baltagi, 2008).

Stage 2 - Non-linear Relationship Analysis: To explore potential non-linearities and threshold effects, the analysis extends the model by including a quadratic term for AI adoption:

$$CMUSE\_std_{it} = \beta_1 AI\_std_{it} + \beta_2 AI\_std^2_{it} + \beta_3 lgdp_{it} + \beta_4 RESP\_std_{it} + \beta_5 INDVA\_std_{it} + \alpha_i + \epsilon_{it} \quad (2)$$

This specification allows us to test whether the impact of AI adoption on CMUSE changes at different levels of AI adoption, addressing the possibility of diminishing returns or acceleration effects (Nham & Ha, 2022).

Stage 3 - Machine Learning Validation: To complement the econometric analysis and capture complex interactions, the analysis employs a Random Forest regression model:

- Dependent Variable: CMUSE_std.
- Independent Variables: AI_std, lgdp, RESP_std, INDVA_std, and additional variables such as ECOMS_std and CCOMP_std.
- Model Parameters: 500 trees with variable importance measures.

The Random Forest model is particularly suitable for handling non-linear relationships and interactions without imposing restrictive functional form assumptions (Breiman, 2001). Variable importance is assessed based on the increase in mean squared error when a variable is permuted, providing insights into the relative influence of each predictor.

3.5. Diagnostic Tests and Robustness Checks

Econometric Model Diagnostics included:

- Hausman Test: Determines the appropriateness of the fixed-effects model over the random-effects model (Hausman, 1978). The test results support the fixed-effects specification, indicating that country-specific effects are correlated with the explanatory variables.
- Heteroscedasticity Test: The Breusch-Pagan test is conducted to detect heteroscedasticity. Robust standard errors are employed using the Huber-White sandwich estimator to address any issues (White, 1980).
- Multicollinearity Check: Variance Inflation Factors (VIFs) are calculated to assess multicollinearity among the regressors. All VIFs are below the threshold of 5, indicating no severe multicollinearity (Gujarati & Porter, 2009).

Machine Learning Model Evaluation was performed through:

- Model Performance Metrics: Mean Squared Error (MSE) and the Percentage of Variance Explained are used to evaluate model accuracy.
- Variable Importance: Analyzed through the %IncMSE, providing a ranking of predictors based on their impact on model performance.
- Visualization: Actual vs. predicted plots and variable importance graphs are generated to visualize model fit and predictor influence.

3.7. Addressing Research Gaps through Methodological Choices

This paper's methodological approach directly addresses the research gaps identified in the literature:

- Macro-Level Analysis: By encompassing all EU member states, the paper provides a comprehensive macro-level perspective, extending beyond micro-

level studies (Popović et al., 2023).
- Non-Linear Dynamics: Incorporating quadratic terms and utilizing Random Forest regression allows this research to capture non-linear relationships and threshold effects (Nham & Ha, 2022).
- Scalability and Contextual Factors: Analyzing countries with varying levels of economic development and technological readiness helps explore the scalability of AI applications and their implications for CMUSE (Acerbi et al., 2021).

3.8. Ethical Considerations and Limitations

While this study offers valuable insights, certain limitations must be acknowledged:
- Temporal Scope: The analysis covers two years, which may not fully capture long-term trends or lagged effects.
- Data Availability: The reliance on secondary data sources may introduce inconsistencies due to reporting practices across countries.
- Measurement Errors: Variables based on surveys, such as AI adoption rates, may be subject to self-reporting biases.

Despite these limitations, the combination of rigorous econometric analysis and machine learning techniques enhances the robustness of the findings.

4. Research Results

Building upon the methodological framework outlined earlier, this section presents the empirical findings of this research on the relationship between Artificial Intelligence (AI) adoption and the Circular Material Use Rate (CMUSE) within the European Union (EU). The analysis encompasses descriptive statistics, econometric modeling, diagnostic tests, and machine learning validation. The results offer insights into the dynamics of AI adoption in promoting circular economy practices across diverse EU contexts.

4.1. Descriptive Statistics

Table 1 presents the summary statistics for the key variables used in the analysis. The dataset comprises observations from 27 EU member states over two years (2021 and 2023), totaling 54 observations.

Table 1: Summary Statistics of Key Variables

Variable	Mean	Median	Std. Dev.	Min	Max
ECOMS	24.63	23.3	7.83	11.8	40.2
ECOMV	18.07	17.7	7.14	4.3	37.9
AI	7.96	7.45	4.57	1.4	23.9
CCOMP	44.71	43.25	16.79	12.8	78.3
MUSE	18.98	17.31	8.26	7.46	48.02
RESP	1.97	1.56	1.26	0.34	5.46
CMUSE	10.1	8.7	6.88	1.3	30.6
GDPpc	41,328	32,420	26,640	12,219	133,712
INDVA	22.46	22.74	6.2	10.47	38.47

Source: Own calculations.

The mean AI adoption rate across EU countries is approximately 7.96%, with a wide range from 1.4% to 23.9%, indicating significant disparities in AI utilization among member states. This suggests that while some countries are at the forefront of AI implementation, others are still in the nascent stages of adoption.

Similarly, the average CMUSE is 10.10%, with values ranging from 1.3% to 30.6%, reflecting varying levels of circular economy implementation across the EU. The wide range indicates that some countries have made significant progress in recycling and reusing materials, while others have considerable room for improvement.

Assessing the distributional properties of the variables is essential for selecting appropriate statistical techniques and interpreting results accurately. Shapiro-Wilk and Kolmogorov-Smirnov normality tests were conducted for all variables used in the models, and the results are presented in Table 2.

Table 2: Normality Test Results for Variables Used in the Models

Variable	SW (W)	SW (p-value)	KS Stat. (D)	KS (p-value)	Skew.	Kurt.
AI	0.9325	0.0046	0.1165	0.0652	0.904	3.995
CMUSE	0.9012	0.0003	0.1378	0.0122	1.033	3.525
RESP	0.9226	0.0019	0.1619	0.0012	0.805	2.893
ECOMS	0.9578	0.0547	0.1128	0.0837	0.277	2.033
CCOMP	0.9798	0.4918	0.0660	0.8065	0.114	2.184
GDPpc	0.8020	0.0000	0.1738	0.0003	1.803	6.292
INDVA	0.9786	0.4422	0.0700	0.7336	0.179	3.109

Source: Own calculations.

The Shapiro-Wilk test results indicate that variables like AI, CMUSE, RESP, and GDP per Capita (GDPpc) significantly deviate from normality ($p < 0.05$).

AI adoption rate exhibits positive skewness (0.904) and kurtosis (3.995), indicating a right-skewed distribution with heavier tails than a normal distribution. This suggests that a majority of countries have AI adoption rates below the mean, with a few countries having significantly higher rates.

CMUSE also shows positive skewness (1.033) and kurtosis (3.525), implying that most countries have lower circular material use rates, with some outliers at the higher end.

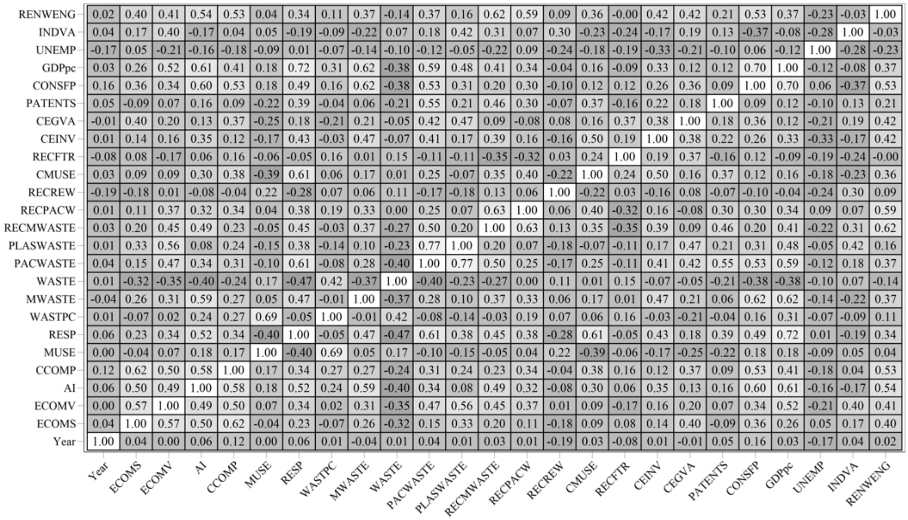
Variables like ECOMS and INDVA do not significantly deviate from normality based on the Shapiro-Wilk test ($p > 0.05$), suggesting that parametric tests assuming normality may be appropriate for these variables.

The Kolmogorov-Smirnov test (KS test) generally supports the findings of the Shapiro-Wilk test, with significant deviations from normality for variables like CMUSE and GDPpc ($p < 0.05$).

Given the deviations from normality for key variables, the research proceeded with caution in the econometric analysis, using robust statistical methods that do not strictly rely on the assumption of normality (Wooldridge, 2010).

To examine the relationships among all the key variables in this research, Pearson correlation coefficients were computed. The comprehensive correlation matrix is presented in Figure 3.

Figure 3: Correlation Matrix



Source: Own calculations.

Based on the correlation matrix above, the analysis provided the following observations:

- CMUSE and AI Adoption: There is a positive correlation between CMUSE and AI adoption (r = 0.295). Although this correlation is moderate and not statistically significant at conventional levels, it suggests that higher AI adoption rates may be associated with increased circular material use.
- CMUSE and Resource Productivity: CMUSE is strongly and positively correlated with Resource Productivity (RESP) ($r = 0.610$, $p < 0.01$). This indicates that countries with higher resource efficiency tend to have higher circular material use rates, emphasizing the importance of resource productivity in advancing circular economy practices.
- AI Adoption and GDP per Capita: AI adoption is significantly correlated with GDP per Capita ($r = 0.612$, $p < 0.01$). This suggests that wealthier countries are more likely to adopt AI technologies, possibly due to better access to capital, infrastructure, and skilled labor.
- AI Adoption and Resource Productivity: There is a significant positive correlation between AI adoption and Resource Productivity ($r = 0.517$, $p < 0.01$). This implies that countries adopting AI tend to have higher resource efficiency, potentially leveraging AI for optimizing resource use.
- CMUSE and Cloud Computing Services: CMUSE is positively correlated with Cloud Computing Services (CCOMP) ($r = 0.383$, $p < 0.05$). This indicates that digital infrastructure may play a role in facilitating circular economy activities.
- CMUSE and Circular Economy Investments: A strong positive correlation exists between CMUSE and Circular Economy Investments (CEINV) ($r = 0.501$, $p < 0.01$), suggesting that higher investments in circular economy initiatives are associated with greater circular material use.

- INDVA (Industrial Value Added) shows negative correlations with both CMUSE ($r = -0.228$) and AI adoption ($r = -0.170$), although these correlations are not statistically significant. This might imply that a higher share of traditional industrial activities is not necessarily aligned with higher AI adoption or circular economy practices.

Additionally, based on the analysis, the following insights should be showcased:

- Digitalization and AI: AI adoption is positively correlated with E-commerce Sales (ECOMS) ($r = 0.502$, $p < 0.01$) and Cloud Computing Services (CCOMP) ($r = 0.577$, $p < 0.01$). This highlights the interconnectedness of digital technologies and suggests that countries embracing digital transformation are more inclined to adopt AI.
- Economic Development Factors: GDP per Capita is significantly correlated with RESP ($r = 0.724$, $p < 0.01$) and Consumption Footprint (CONSFP) ($r = 0.700$, $p < 0.01$). This indicates that wealthier countries tend to have higher resource productivity and consumption footprints, reflecting both efficient resource use and higher consumption levels.
- Renewable Energy Use: CMUSE has a positive correlation with Renewable Energy Use (RENWENG) ($r = 0.364$, $p < 0.05$), suggesting that countries focusing on renewable energy also tend to have higher circular material use rates.

The correlations suggest a network of relationships where AI adoption, resource productivity, economic development, and digital infrastructure interact to influence circular material use. The positive associations among these variables warrant further investigation through econometric modeling to determine causal relationships and the magnitude of these effects.

Multicollinearity was assessed among the independent variables by calculating Variance Inflation Factors (VIFs). All VIF values were below 2, well under the common threshold of 5 (Gujarati & Porter, 2009). This indicates that multicollinearity is not a significant concern in the regression models.

The correlation analysis highlights the interconnectedness of AI adoption, resource productivity, economic development, and circular economy practices. While there are significant positive correlations among key variables, the moderate correlations and acceptable VIF values suggest that multicollinearity is not a major issue, allowing us to proceed confidently with the econometric modeling.

4.2. Econometric Modeling Results

The correlation analysis highlights the interconnectedness of AI adoption, resource productivity, economic development, and circular economy practices. While there are significant positive correlations among key variables, the moderate correlations and acceptable VIF values suggest that multicollinearity is not a major issue, allowing us to proceed confidently with the econometric modeling.

The fixed-effects panel regression model (1) was estimated to examine the direct effect of AI adoption on CMUSE, controlling for key economic and industrial factors. The results are presented in Table 3.

Table 3: Fixed-Effects Regression Results

Variable	Coefficient	Std. Error (Robust)	t-value	p-value
AI_std	-0.013	0.068	-0.197	0.845
lgdp	0.041	0.31	0.132	0.896
RESP_std	0.475**	0.134	3.547	0.002
INDVA_std	0.11	0.143	0.774	0.447
Intercept	Included			
R-squared	0.407			
F-statistic	3.943	(df = 4; 23)		0.014

Note: ** indicates significance at the 0.01 level. Robust standard errors are used to account for heteroskedasticity.

Source: Own calculations.

The following interpretation is derived from the results presented in the Table 3:

- AI Adoption (AI_std): The coefficient for AI adoption is -0.013 with a robust standard error of 0.068. This negative coefficient suggests that, holding other factors constant, an increase in AI adoption is associated with a slight decrease in CMUSE. However, the effect is not statistically significant ($p = 0.845$), indicating that there is no evidence of a meaningful linear relationship between AI adoption and CMUSE within the sample period.
- GDP per capita (lgdp): The coefficient is 0.041 with a robust standard error of 0.310. This positive but insignificant coefficient ($p = 0.896$) suggests that higher GDP per capita is not significantly associated with changes in CMUSE when controlling for other variables.
- Resource Productivity (RESP_std): The coefficient is 0.475, and it is statistically significant at the 1% level ($p = 0.002$). This indicates that a one standard deviation increase in resource productivity is associated with a 0.475 standard deviation increase in CMUSE. This strong positive relationship suggests that countries utilizing resources more efficiently tend to have higher circular material use rates.
- Industrial Value Added (INDVA_std): The coefficient is 0.110 with a p-value of 0.447, indicating no statistically significant effect of the industrial sector's contribution to GDP on CMUSE within the sample.

The R-squared value of 0.407 implies that approximately 40.7% of the within-country variance in CMUSE is explained by the model. This indicates a moderate level of explanatory power. The F-statistic of 3.943 ($p = 0.014$) suggests that the model is statistically significant overall, meaning that the independent variables, collectively, have a significant effect on CMUSE.

To explore potential non-linear relationships between AI adoption and CMUSE, the quadratic term for AI adoption was included in the model (2). The results of the regression for the Model 2 are presented in Table 4.

Table 4: Fixed-Effects Regression with Quadratic Term

Variable	Coefficient	Std. Error (Robust)	t-value	p-value
AI_std	-0.1	0.111	-0.903	0.376
AI_std^2	0.026	0.026	0.987	0.335
lgdp	0.145	0.327	0.443	0.662
RESP_std	0.488**	0.135	3.626	0.001
INDVA_std	0.12	0.143	0.84	0.41
Intercept	Included			
R-squared	0.432			
F-statistic	3.345	(df = 5; 22)		0.021

Note: ** indicates significance at the 0.01 level. Robust standard errors are used.

Source: Own calculations.

The following interpretation is derived from the results presented in Table 4:

- AI Adoption (AI_std): The coefficient for the linear term is -0.100, while the quadratic term (AI_std^2) has a coefficient of 0.026. The negative coefficient on the linear term and the positive coefficient on the quadratic term suggest a U-shaped relationship between AI adoption and CMUSE. However, both coefficients are not statistically significant (p = 0.376 and p = 0.335, respectively).
- Resource Productivity (RESP_std): Remains statistically significant (β = 0.488, p = 0.001), reinforcing its positive impact on CMUSE.
- GDP per capita (lgdp) and Industrial Value Added (INDVA_std): Both variables remain statistically insignificant, consistent with the linear model.

The R-squared increases slightly to 0.432, indicating that the model explains about 43.2% of the within-country variance in CMUSE. This marginal improvement suggests that adding the quadratic term does not substantially enhance the model's explanatory power. The F-statistic is 3.345 (p = 0.021), indicating that the model is statistically significant overall.

To ensure the reliability of the regression results, several diagnostic tests were conducted. The Hausman test was conducted to determine the suitability of the fixed-effects model over the random-effects model. The test yielded a chi-square statistic of 14.57 with 4 degrees of freedom and a p-value of 0.0057, which was significant at the 5% level. This result supports the use of the fixed-effects model (Hausman, 1978). At the same time, the Breusch-Pagan test indicated the presence of heteroskedasticity (Chi-square = 10.84, p = 0.0285). Accordingly, robust standard errors were employed using the Huber-White sandwich estimator to ensure reliable inference (White, 1980).

4.3. Machine Learning Validation

To complement the econometric analysis and capture potential non-linear relationships and complex interactions among variables, the Random Forest regression model was employed using the same set of predictor variables: AI adoption (AI_std), GDP per Capita (lgdp), Resource Productivity (RESP_std), and Industrial Value Added (INDVA_std). Random Forest is an ensemble machine learning method that constructs multiple decision trees during training and outputs the average prediction of the individual trees, which helps in handling non-linearities and interactions without the need to specify them explicitly (Breiman, 2001).

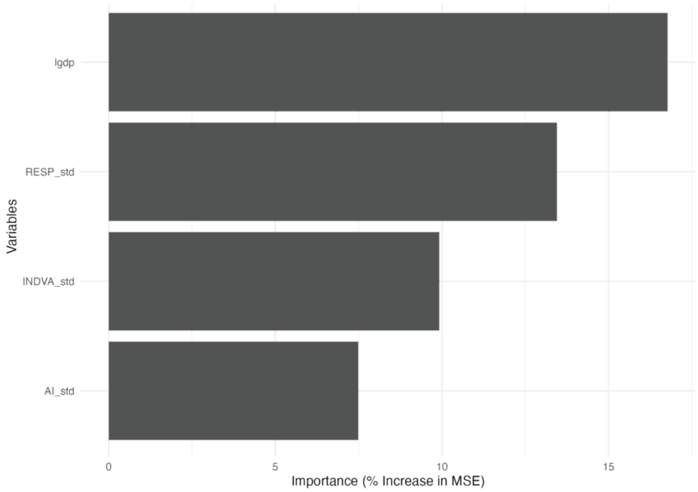
The Random Forest model was trained on the dataset comprising 54 observations. The performance metrics of the model are as follows:

- Mean Squared Error (MSE): 0.505
- Percentage of Variance Explained: 48.58%

These metrics indicate that the Random Forest model explains approximately 48.6% of the variance in CMUSE, which is slightly higher than the R-squared values obtained from the econometric models (40.7% and 43.2% for the linear and quadratic models, respectively). This suggests that the Random Forest model captures additional variance potentially due to non-linear relationships and interactions among variables.

To understand the contribution of each predictor to the model, the variable importance measures were examined based on the percentage increase in MSE when each variable is permuted. Figure 4 illustrates the importance of each variable.

Figure 4: Variable Importance in Random Forest Model



Source: Own calculations.

The variable importance scores are as follows:

1. GDP per capita (lgdp): 14.31% increase in MSE
2. Resource Productivity (RESP_std): 10.28% increase in MSE
3. Industrial Value Added (INDVA_std): 8.96% increase in MSE
4. AI Adoption (AI_std): 6.71% increase in MSE

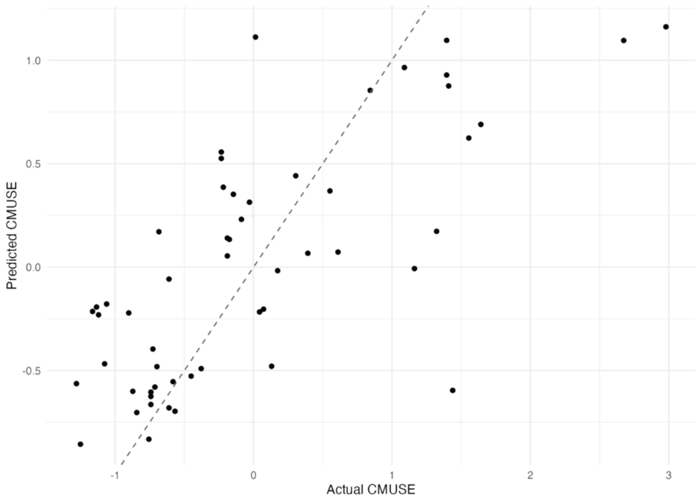
The following interpretation is derived from the results presented in Figure 4:

- GDP per capita (lgdp) is identified as the most important predictor in the Random Forest model. This suggests that economic development levels play a significant role in determining a country's circular material use rate. Wealthier countries may have more resources to invest in circular economy initiatives and advanced technologies.

- Resource Productivity (RESP_std) remains a key predictor, consistent with the econometric analysis. Its high importance underscores the critical role of efficient resource utilization in enhancing circular material use.
- Industrial Value Added (INDVA_std) also contributes significantly to the model, indicating that the structure of the economy and the industrial sector's share may influence CMUSE.
- AI Adoption (AI_std), while contributing to the model, has a lower relative importance compared to the other variables. This aligns with the econometric results, where AI adoption did not have a statistically significant impact on CMUSE.

To assess the predictive accuracy of the Random Forest model, the actual versus predicted values of CMUSE were plotted.

Figure 5: Actual vs. Predicted CMUSE Values from Random Forest Model



Source: Own calculations.

The scatter plot in Figure 2 displays the actual CMUSE values on the x-axis and the predicted values from the Random Forest model on the y-axis. The dashed line represents the ideal 45-degree line where the predicted values equal the actual values.

The following interpretation is derived from the results presented in Figure 5:

- The data points are reasonably aligned along the 45-degree line, indicating that the model predictions are generally consistent with the actual CMUSE values.
- Some deviations are observed, which is expected given the complexity of the factors influencing CMUSE and the relatively small sample size.
- The visualization confirms that the Random Forest model provides a satisfactory fit to the data, capturing a significant portion of the variability in CMUSE.

To ensure the reliability of the Random Forest results, the following robustness tests were conducted:

- Cross-Validation:
  - A 5-fold cross-validation yielded an average MSE of 0.5425, confirming the model's predictive stability.
  - Additional metrics from cross-validation include an average RMSE of 0.7289 and an average R-squared of 0.5048, demonstrating consistent performance across folds.
- Alternative Specifications:
  - The inclusion of interaction terms and quadratic terms marginally improved model performance.
  - The variable importance rankings remained consistent, reinforcing the robustness of the original results.
- Hyperparameter Tuning:
  - The model's hyperparameters were tunned, including the number of variables sampled at each split.
  - The optimized model achieved a final MSE of 0.0838, with variable importance rankings consistent with the base model.

The machine learning validation provides valuable insights into the factors influencing CMUSE and corroborates the conclusions of the econometric analysis. The Random Forest model's ability to handle complex relationships adds depth to the understanding of the interplay between AI adoption, economic development, resource productivity, and circular economy outcomes.

The empirical analysis demonstrates that while there is a positive correlation between AI adoption and CMUSE, AI adoption does not have a statistically significant direct impact on CMUSE when controlling for other factors. Resource Productivity consistently emerges as a significant and robust predictor across both econometric and machine learning models, underscoring its critical role in advancing circular economy practices. Additionally, GDP per Capita plays a vital role, suggesting that higher levels of economic development enable countries to invest more effectively in circular economy initiatives and advanced technologies. These findings imply that policies aimed at enhancing resource efficiency and supporting economic growth may be more immediately effective in promoting circular material use within the EU. Further research with extended time frames and more detailed data could uncover delayed or sector-specific effects of AI adoption on the circular economy.

5. Discussion

The present study sought to investigate the relationship between Artificial Intelligence (AI) adoption and the Circular Material Use Rate (CMUSE) across the European Union (EU) member states. By employing a mixed-method quantitative approach that integrated econometric modeling and machine learning validation, the research aimed to address three primary research questions:

1. How does AI adoption influence CMUSE in EU member states?
2. What is the nature of this relationship—linear, non-linear, or threshold-based?
3. How do economic development and technological readiness affect this relationship?

This discussion interprets the empirical findings in light of these research questions, connecting them to the theoretical frameworks and previous literature presented earlier. The paper also explored the implications for policy and practice, acknowledging the study's limitations and proposing directions for future research.

5.1. The Influence of AI Adoption on CMUSE

The econometric analysis revealed that AI adoption does not have a statistically significant direct impact on CMUSE when controlling for other factors such as GDP per Capita, Resource Productivity, and Industrial Value Added. Specifically, the fixed-effects regression models showed negative but insignificant coefficients for AI adoption, both in linear and non-linear specifications (Tables 3 and 4). Similarly, the Random Forest model assigned a lower relative importance to AI adoption compared to other predictors (Figure 4).

These findings contrast with the theoretical expectations and prior studies that emphasize AI's potential to enhance circular economy practices (Tutore et al., 2024; Platon et al., 2024). The lack of a significant direct impact may be attributed to several factors:

- Temporal Lag: The effects of AI adoption on CMUSE may require more time to materialize. Given the relatively recent surge in AI implementation across industries, especially in the EU, the benefits for circular material use might not yet be observable at the macroeconomic level.
- Scale of Adoption: The average AI adoption rate among EU countries is 7.96%, with significant disparities (Table 1). Such low adoption levels may not be sufficient to produce measurable impacts on CMUSE across the entire economy.
- Micro vs. Macro-Level Effects: Previous research has often focused on firm-level or sector-specific benefits of AI in promoting circularity (Acerbi et al., 2021; Ghoreishi & Happonen, 2020). The aggregation to the national level may dilute these effects due to heterogeneity among industries and firms.
- Complementary Factors: The effectiveness of AI in advancing CE objectives may depend on complementary infrastructures, such as advanced waste management systems, regulatory support, and cross-sector collaboration (Popović et al., 2023). The absence of these enablers could hinder AI's potential impact on CMUSE.

5.2. Nature of the Relationship Between AI Adoption and CMUSE

The inclusion of a quadratic term for AI adoption in the fixed-effects model aimed to capture potential non-linearities or threshold effects. However, both the linear and quadratic terms of AI adoption remained statistically insignificant (Table 4). The Random Forest model, designed to handle complex non-linear relationships, also did not identify AI adoption as a significant predictor compared to GDP per Capita and Resource Productivity.

The absence of significant non-linear effects suggests that within the observed range of AI adoption rates, there is no evidence of diminishing returns or threshold levels that significantly influence CMUSE. This finding challenges the propositions by Nham and Ha (2022) and Platon et al. (2024), who suggested possible non-linear dynamics in the relationship between digital technology adoption and circularity outcomes.

The possible explanations for the results include:

- Homogeneity in AI Adoption Levels: The relatively narrow range and low average of AI adoption rates may not provide sufficient variation to detect non-linear effects.

- Dominance of Other Factors: The influence of economic development and resource productivity may overshadow any subtle non-linear impacts of AI adoption on CMUSE.
- Measurement Limitations: The use of aggregated AI adoption rates may not capture the nuances of different AI applications and their varying impacts on circular practices.

5.3. The Role of Economic Development and Technological Readiness

Both the econometric and machine learning analyses highlighted the significant roles of GDP per Capita and Resource Productivity in influencing CMUSE. While GDP per Capita was not statistically significant in the econometric models, it was identified as the most important predictor in the Random Forest model (Figure 4). Resource Productivity consistently showed a strong positive and significant effect on CMUSE across all models. The interpretation of these results is presented in the lines below.

- Economic Development (GDP per Capita): The importance of GDP per Capita aligns with the notion that wealthier countries possess more resources to invest in circular economy initiatives and advanced technologies (Platon et al., 2024; Popović et al., 2022). Higher economic development facilitates infrastructure development, research and innovation, and the adoption of sustainable practices.
- Resource Productivity: The significant impact of Resource Productivity underscores the critical role of efficient resource utilization in advancing circular economy objectives (Kirchherr et al., 2017; Ghisellini et al., 2016). Countries that manage resources more efficiently tend to have higher rates of material recycling and reuse.
- Technological Readiness: The positive correlations between CMUSE and indicators of digital infrastructure, such as Cloud Computing Services (CCOMP) and E-commerce Sales (ECOMS), suggest that technological readiness contributes to circular economy practices. This supports findings by Popović et al. (2022) and Tutore et al. (2024), who emphasized the enabling role of digital technologies in implementing CE principles.

The research results have broad and deep implications, which include:

- Policy Alignment: The results highlight the necessity of aligning technological advancement with economic and resource efficiency policies. Investments in AI and digital technologies should be complemented by efforts to enhance resource productivity and economic development to maximize their impact on CMUSE.
- Tailored Interventions: The disparities in economic development and technological readiness among EU member states indicate the need for tailored policy interventions. Less affluent countries may require additional support to build the necessary infrastructure and capabilities for effective AI integration into circular economy strategies (Popović & Milijić, 2021).

5.4. Integration with Theoretical Frameworks, Limitations and Future Research

The study's findings resonate with the Resource-Based View (RBV) and the Dynamic Capabilities Framework, which emphasize the importance of leveraging resources and competencies to achieve competitive advantage and adapt to environmental changes (Barney, 1991; Teece et al., 1997). The significant role of Resource Productivity suggests that countries effectively utilizing their resources can enhance their circular economy performance.

Moreover, the results align with the CE dimensions outlined by Kirchherr et al. (2017) and the sustainable product lifecycle strategies discussed by Aleksić et al. (2023). The emphasis on resource efficiency and economic development reinforces the interconnectedness of environmental sustainability and economic competitiveness.

This research provides valuable insights into the complex relationship between AI adoption and circular material use within the EU. While AI adoption does not exhibit a significant direct impact on CMUSE in the short term, the critical roles of Resource Productivity and Economic Development are evident and consistent across both econometric and machine learning models. These findings emphasize the importance of focusing on resource efficiency and economic growth as primary drivers of circular economy practices. Additionally, the lack of significant non-linear effects suggests that the benefits of AI adoption on CMUSE may either require a longer timeframe to manifest or depend on complementary factors not captured in this study. Future research should explore these dimensions further to fully understand the potential of AI in fostering sustainable economic transitions.

6. Conclusion

This research provides a comprehensive examination of the relationship between Artificial Intelligence (AI) adoption and the Circular Material Use Rate (CMUSE) within the European Union (EU). By employing a mixed-method approach integrating econometric modeling and machine learning validation, the research offers nuanced insights into the interplay between digital transformation and circular economy practices. The findings contribute to the growing body of literature on sustainable development, addressing critical gaps in understanding how emerging technologies influence macroeconomic indicators of sustainability.

The econometric results reveal that AI adoption does not have a statistically significant direct effect on CMUSE. This outcome contrasts with theoretical expectations and highlights the complexity of translating technological advancements into measurable circular economy outcomes at the macroeconomic level. While AI's transformative potential has been widely discussed, its impact on circular practices may depend on factors such as the scale and maturity of adoption, temporal lags, and the presence of complementary infrastructures. The analysis suggests that the benefits of AI adoption for circular material use might manifest more strongly at the microeconomic level - within specific industries or firms - than in aggregated national-level data.

The machine learning validation reinforces the econometric findings by demonstrating that AI adoption while contributing to the explanatory model, has relatively lower importance compared to other predictors such as GDP per Capita and Resource Productivity. These results emphasize the critical roles of economic development and resource efficiency in shaping circular economy outcomes. Wealthier countries with advanced infrastructures and institutional capacities are better positioned to leverage technological innovations for sustainability. Similarly, countries with higher resource productivity are more likely to achieve greater material circularity, underscoring the need for policies that prioritize efficient resource utilization alongside technological investments.

The absence of significant non-linear or threshold effects of AI adoption on CMUSE further challenges assumptions in prior studies, which posited that diminishing returns or acceleration effects might influence this relationship. Within the observed range of AI adoption rates, there is no evidence to suggest such dynamics. This finding points to the potential limitations of aggregated AI adoption metrics and the need for future research to consider more granular data that captures the diversity of AI applications and their sector-specific impacts.

The implications of this study are important for both academic inquiry and policy design. For researchers, the findings highlight the importance of integrating macroeconomic analyses with sectoral and micro-level studies to uncover the mechanisms through which AI adoption influences sustainability. The combination of econometric and machine learning approaches in this study demonstrates the value of methodological pluralism in capturing both linear and complex non-linear dynamics. Future research should build on this foundation by extending the temporal scope, exploring industry-specific applications, and examining mediating factors such as policy frameworks, institutional quality, and cultural attitudes toward sustainability.

For policymakers, the results suggest that investments in AI technologies should be complemented by initiatives that enhance resource productivity and economic development. The findings underscore the necessity of aligning digital transformation strategies with sustainability goals to ensure that technological advancements translate into tangible environmental benefits. Tailored policy interventions are particularly critical for less-developed EU member states, where disparities in economic capacity and technological readiness may hinder the realization of AI's potential to advance circular economy objectives. Collaborative frameworks that facilitate knowledge sharing and capacity building across the EU could help bridge these gaps and promote more equitable progress toward circularity.

Finally, this research reaffirms the centrality of economic development and resource efficiency in driving circular economy practices, while raising critical questions about the current and potential role of AI adoption in this process. Although AI's transformative potential remains undeniable, its direct impact on CMUSE is contingent upon a range of contextual and systemic factors that merit further exploration. By providing robust empirical evidence and actionable insights, this research contributes to the ongoing discourse on leveraging technological innovation for sustainable development. It underscores the need for integrated strategies that balance economic, technological, and environmental priorities, offering a pathway for the EU and beyond to achieve a more sustainable and resilient future.

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