Artificial Intelligence Adoption, Circular Material Use, and Resource Productivity in the European Union

***Șopea-Iordache A.M.**
Petroleum-Gas University of Ploiesti, 100680 Ploiești, Romania/Valahia University Of Târgoviște, Sinaia Alley 13, Târgoviște 130004;
andreea.sopea@upg-ploiesti.ro/maria.iordache.mg@valahia.ro

Declaration on AI-assisted preparation: OpenAI ChatGPT was used to assist with language editing and grammar. The author is responsible for checking all information from the manuscript.

ABSTRACT

This study examines whether enterprise artificial intelligence (AI) adoption and circular material use are associated with resource productivity across the 27 European Union Member States. Although digital technologies may support resource optimization, their diffusion does not necessarily translate into measurable circular-economy outcomes. Using a harmonized 2024 cross-section from six Eurostat datasets (N = 27), we estimate ordinary least squares models with HC3 heteroskedasticity-robust standard errors. Resource productivity (euros per kilogram) is related to enterprise AI adoption, circular material use, gross fixed capital formation as a share of GDP, research and development expenditure, and, in sensitivity specifications, GDP per capita. An AI × circular-material-use interaction tests the proposed complementarity. In the baseline model, circular material use is positively associated with resource productivity ($\beta = 0.1016$, HC3 $p = 0.0043$), whereas AI adoption is not statistically significant ($\beta = 0.0789$, $p = 0.177$). Investment intensity has a negative baseline coefficient ($\beta = -0.1786$, $p = 0.0285$), contrary to the directional hypothesis. The interaction is positive but not significant in the full model ($\beta = 0.00260$, $p = 0.402$), and leave-one-country-out tests do not overturn that conclusion. The analysis supports a conditional association between circular material use and resource productivity but does not establish an independent AI effect or AI-circularity synergy. The findings are associative, not causal; they do not directly measure green finance or competitiveness.

Keywords: *artificial intelligence, circular economy, resource productivity, sustainable finance, European Union*

JEL Classification: O33, Q56, O47, E22

1. INTRODUCTION

The transition from a linear economic model toward a circular economy has become an important component of contemporary sustainability strategies. The traditional linear system of production and consumption relies on continuous extraction of natural resources, transformation into products, consumption, and disposal. In contrast, the circular economy seeks to retain the value of products, materials, and resources for as long as possible by slowing, narrowing, and closing resource flows. Circular strategies include reuse, recycling, repair, maintenance, refurbishment, remanufacturing, and other mechanisms that reduce dependence on virgin resources and minimize waste generation (Hofmann & Jaeger-Erben, 2020).

The circular economy is not limited to waste management. It requires changes in production systems, organizational practices, business models, investment decisions, and innovation processes. Lindgreen et al. (2020) argue that one of the central ambitions of circularity is to decouple economic development from finite resource consumption while simultaneously reducing environmental pressures and maintaining economic value creation. Their review also shows that circular-economy assessment approaches remain highly diverse and that only a relatively limited number integrate environmental, economic, and social dimensions simultaneously. The issue of measurement is particularly important because circularity cannot be evaluated solely through individual recycling or waste indicators. Helander et al. (2019) show that many circular-economy indicators focus on single activities and do not necessarily capture the broader environmental pressures associated with economic activity. They therefore recommend complementing activity-based circular-economy indicators with broader measures related to resource use and environmental pressure. This observation supports the use of resource productivity as an outcome variable because it connects the economic value generated by an economy with its material-resource consumption.

Evidence from European economies also indicates that circularity is closely related to innovation and economic development. Šverko Grdić et al. (2020) analyse circular-economy indicators in EU countries and emphasize the relevance of indicator groups covering production and consumption, waste management, secondary raw materials, competitiveness, and innovation. Their study confirms the usefulness of national-level indicators for analysing differences in circular-economy performance and its relationship with economic development. Hysa et al. (2020) provide an important empirical foundation by examining circular-economy indicators and economic growth in European countries. Their model includes environmental taxes, recycling, private investment and employment in circular-economy sectors, patents

related to recycling, and trade in recyclable raw materials. Using fixed-effects panel estimation and an Arellano-Bond dynamic model, they report positive relationships between circular-economy dimensions, innovation, investment, and economic growth. Their findings further indicate that resource productivity and environmental innovation are relevant for explaining differences in economic growth across EU economies.

At the same time, artificial intelligence has become a major component of digital transformation. AI is increasingly considered a general-purpose technology capable of influencing tasks, organizational processes, business models, and innovation systems. Jöhnk et al. (2021) stress that AI can create new business opportunities and competitive advantages, but successful adoption depends on organizational readiness and the capacity to integrate AI into core activities. Their research identifies strategic alignment, organizational resources, knowledge, culture, and data as central categories of AI readiness.

This distinction is important because AI should not be treated as an automatic source of productivity. Technological adoption requires complementary capabilities. Shi et al. (2020), examining knowledge transfer in AI industry innovation networks, show that innovation performance depends on factors such as network characteristics, organizational culture, willingness to receive knowledge, and absorptive capacity. Thus, technological diffusion and productive outcomes are mediated by organizational and knowledge-related conditions. The relationship between AI and circularity becomes especially relevant when information is considered. Bianchini et al. (2019) identify information availability as a key condition for implementing circular business models. Information about resource condition, material and energy flows, asset use, and product location can support predictive maintenance, process optimization, reuse, remanufacturing, and the identification of previously unexploited circular opportunities. The authors also argue that technologies associated with Industry 4.0 can support continuous data collection, processing, and exchange, thereby improving circular-economy implementation and reducing uncertainty in circular investment decisions.

The financial dimension is also central to sustainable transformation. Ziolo et al. (2019) argue that finance can act as a driver of sustainability when financial systems incorporate environmental, social, and governance considerations into decision-making and risk assessment. Their framework expands the traditional financial-system perspective beyond efficiency and stability to include sustainability and ESG integration. De Lucia et al. (2020) further show that ESG practices and environmental innovation are associated with financial

performance among European public enterprises, although they also note that sustainability-related investments may require long-term financial commitments and may produce different short- and medium-term effects.

Previous studies of EU economies have examined the relationships between circular-economy indicators, innovation, and economic growth (Hysa et al., 2020; Šverko Grdić et al., 2020), while research on AI has primarily focused on organizational readiness and the capabilities required for successful technology adoption (Jöhnk et al., 2021). However, these research streams have largely been examined separately, leaving limited empirical evidence on whether enterprise AI adoption and circular material use are jointly associated with resource productivity across EU Member States, particularly whether AI adoption strengthens the circularity-resource productivity relationship. This study addresses this gap by examining their individual associations and interaction using harmonized Eurostat data for all 27 EU Member States in 2024.

2. AIMS, RESEARCH QUESTIONS, AND HYPOTHESES

The main aim of this study is to examine how artificial intelligence (AI) adoption and circular-economy performance are associated with resource productivity across the 27 European Union Member States. Building on previous research linking circular-economy indicators with economic performance and research examining the organizational conditions of AI adoption, the study investigates whether these two dimensions are independently associated with resource productivity and whether AI adoption strengthens the relationship between circular material use and resource productivity.

To achieve this aim, three specific objectives are established:

- To assess the association between enterprise AI adoption and resource productivity across EU Member States.
- To examine the relationships between circular material use, investment intensity, and resource productivity, accounting for differences in innovation capacity and economic development.
- To investigate whether enterprise AI adoption moderates the relationship between circular material use and resource productivity.

These objectives are addressed through the following research questions:

RQ1: How is enterprise AI adoption associated with resource productivity across EU Member States?

RQ2: How are circular material use and investment intensity associated with resource productivity across EU Member States?

RQ3: Does enterprise AI adoption positively moderate the relationship between circular material use and resource productivity across EU Member States?

Drawing on the theoretical arguments concerning technological capabilities, circular-economy transformation, and investment, the following hypotheses are formulated:

H1: Enterprise AI adoption is positively associated with resource productivity across EU Member States.

H2a: Circular material use is positively associated with resource productivity across EU Member States.

H2b: Investment intensity is positively associated with resource productivity across EU Member States.

H3: Enterprise AI adoption positively moderates the relationship between circular material use and resource productivity, such that the positive association between circular material use and resource productivity is stronger in Member States with higher levels of AI adoption.

3. THEORETICAL BACKGROUND

The study draws on the general-purpose technology perspective (Bresnahan & Trajtenberg, 1995) and a complementary-capabilities interpretation of organizational resource use. AI can potentially be deployed across many activities, but its benefits depend on data availability, skills, management, and investment in complementary systems. Jöhnk et al. (2021) identify these readiness conditions, while Shi et al. (2020) demonstrate the relevance of knowledge-transfer capacity in AI innovation networks. Accordingly, an observed country-level AI adoption percentage is a measure of diffusion rather than an index of implementation quality.

Circular material use represents a distinct operational dimension: the share of overall material use supplied by recovered materials. It can rise through collection, sorting, processing, reuse, and substitution, but these activities do not necessarily occur in the same enterprises that adopt AI. The proposed moderation mechanism requires a connection between digital information capabilities and actual circular processes. Bianchini et al. (2019) argue that information about material flows and product conditions can enable circular business models. That mechanism motivates H3, without guaranteeing a positive national-level interaction.

Investment and R&D expenditure capture broader enabling conditions. Aggregate gross fixed capital formation measures economy-wide capital formation, not sustainable finance, and may reflect construction, machinery, or other activities with different resource implications. R&D intensity is a proxy for innovation capacity, not a direct measure of circular innovation. The model thus tests associations between observable macroeconomic proxies rather than direct effects of AI-enabled circular projects or green-finance instruments. Gross fixed capital formation can support resource productivity when new capital replaces inefficient machinery or improves production technology, but the opposite association is plausible where investment expands construction or material-intensive infrastructure. Accordingly, the investment hypothesis is directional rather than mechanically assured. Ziolo et al. (2019) provide a sustainability-oriented financial framework, but INV does not operationalize sustainable finance and cannot identify green investment.

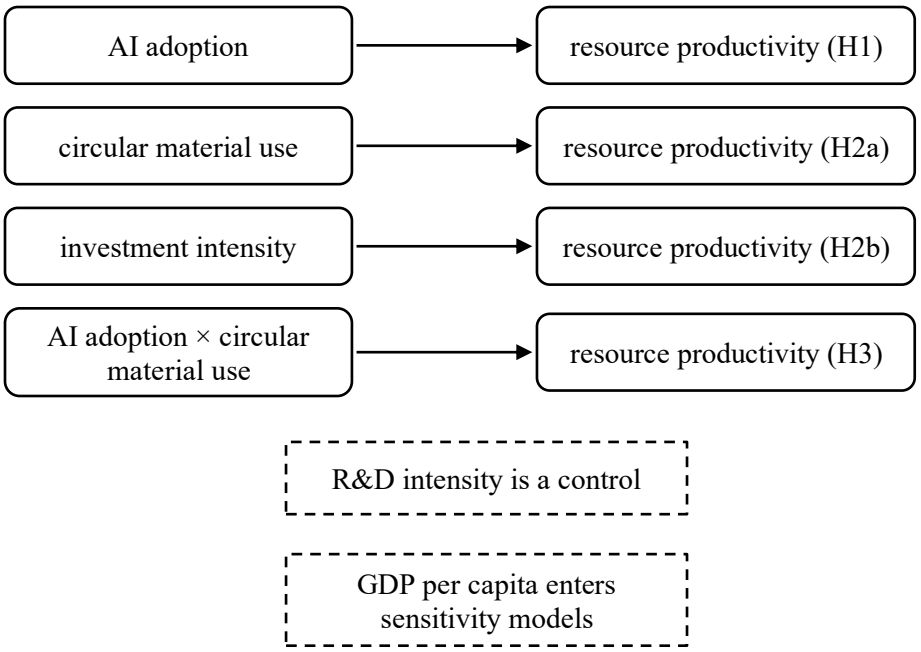

Figure 1. Conceptual Pathways (Hypothesized)

4. METHODS

The unit of observation is the EU Member State in 2024. The final balanced cross-section includes all 27 Member States (N = 27), with no missing values in the selected series. The year was chosen because the enterprise AI indicator

is available for the same reference year as the circularity and national-accounts indicators, avoiding unsupported assumptions about a longer annual panel.

Table 1. Variable Definitions, Measurement Units, and Eurostat Data Sources

Variable	Eurostat code	Measurement
RP	cei_pc030	Resource productivity, €/kg; chain-linked volumes (2015)
AI	isoc_eb_ai	Enterprises using at least one AI technology, 10+ persons employed, %
CMU	cei_srm030	Circular material use rate, %
INV	nama_10_gdp	Gross fixed capital formation / GDP × 100, current-price million €
GDPpc	nama_10_pc	GDP per capita, current-price €/person
R&D	rd_e_gerdtot	Gross domestic R&D expenditure, all sectors, % GDP

Note. RP = resource productivity; AI = enterprise artificial intelligence adoption; CMU = circular material use rate; INV = investment intensity; GDPpc = GDP per capita; R&D = research and development expenditure. Resource productivity uses chain-linked volumes (2015), in €/kg. AI and CMU are percentages; INV and R&D are percentages of GDP; GDPpc is current-price €/person. INV = 100 × gross fixed capital formation / GDP. All indicators refer to 2024.

The study uses harmonized Eurostat exports and retains each variable in its documented unit. There is no interpolation, zero-imputation, or averaging across years. Resource productivity is the ratio of GDP to domestic material consumption, expressed here in euros per kilogram using the chain-linked-volume (2015) Eurostat series. Because GDP is also the numerator of GDP per capita, GDPpc is included only in sensitivity specifications and is not treated as an independent validation of the resource-productivity association.

Investment intensity was calculated from two compatible current-price national-accounts series as 100 × gross fixed capital formation / GDP. The interaction was calculated as AI × CMU using the original percentage-point scales; no artificial conversion to a common physical unit was imposed. All coefficients therefore refer to a one-percentage-point increase in the corresponding percentage variable, conditional on other regressors. The RP series is based on chain-linked-volume output, whereas GDPpc uses current-price GDP, which also calls for care when interpreting their association.

$$RP_i = \beta_0 + \beta_1 AI_i + \beta_2 CMU_i + \beta_3 INV_i + \beta_4 R\&D_i + \beta_5 GDPpc_i + \beta_6 (AI \times CMU)_i + \varepsilon_i \quad (1)$$

In Equation (1), i denotes an EU Member State, ε_i is the regression disturbance, and the year index is omitted because the data comprise a single 2024 cross-section. Coefficients for omitted variables are constrained to zero in the reduced specifications.

Four nested ordinary least squares specifications were estimated: M1 includes AI, CMU, INV, and R&D; M2 adds GDPpc; M3 adds AI × CMU to M2; and M4 adds AI × CMU to M1, omitting GDPpc. The full interaction specification includes all explanatory variables, GDP per capita is excluded from M1 and M4, while the interaction term is excluded from M1 and M2. The country subscript i is used because the dataset is cross-sectional rather than longitudinal.

Inference uses HC3 heteroskedasticity-robust standard errors and residual-degrees-of-freedom t tests. Reported tests include Breusch-Pagan and White diagnostics for heteroskedasticity, Jarque-Bera residual-normality tests, RESET specification checks, variance inflation factors, Cook's distance, leverage, studentized residuals, and leave-one-country-out re-estimation. Interaction effects are interpreted using conditional marginal effects with HC3 confidence intervals. Computations were performed using Python (statsmodels and associated numerical libraries), and country-level input values and outputs are retained in the accompanying reproducibility workbook.

A key measurement concern is that resource productivity uses GDP relative to material consumption, while GDPpc also contains GDP. Adding GDPpc may therefore introduce a mechanical association. M1 and M4, which exclude GDPpc, are central robustness specifications. Even without that overlap, simultaneity, reverse causality, sectoral structure, national price levels, and unobserved institutional differences prevent a causal interpretation.

5. RESULTS

Descriptive statistics show considerable variation among Member States. Average resource productivity is 2.181 €/kg (standard deviation 1.380), and mean enterprise AI adoption is 14.279% (standard deviation 7.177). The full sample contains 27 countries, with no missing observations. The Pearson correlation between AI adoption and RP is 0.534, while the CMU-RP correlation is 0.639. These positive bivariate associations are not equivalent to conditional regression effects.

The baseline model explains 63.8% of cross-country variation in RP (adjusted $R^2 = 0.572$). CMU is positively associated with RP ($\beta = 0.1016$, $p = 0.0043$), while AI is positive but not significant ($\beta = 0.0789$, $p = 0.177$). Investment intensity is negative ($\beta = -0.1786$, $p = 0.0285$), contrary to H2b. Adding GDPpc increases R^2 to 0.832, but this must be considered alongside the GDP-overlap concern. The full interaction model has $R^2 = 0.841$ (adjusted $R^2 = 0.794$), only a modest improvement over M2.

Table 2. Descriptive Statistics for the EU-27 Sample, 2024

Indicator	N	Mean	SD	Min	Max
RP_EUR_kg	27	2.181	1.380	0.386	5.739
AI_pct	27	14.279	7.177	3.070	27.580
CMU_pct	27	10.919	7.629	1.300	32.700
INV_pctGDP	27	21.275	2.745	16.627	26.620
RD_pctGDP	27	1.798	0.933	0.460	3.530
GDPpc_EUR	27	41855.185	25879.020	16340.000	128710.000

Note. N = number of countries; SD = standard deviation; Min = minimum; Max = maximum. RP is €/kg; AI and CMU are percentages; INV and R&D are percentages of GDP; GDPpc is current-price €/person. The sample covers all 27 EU Member States in 2024, without missing observations.

Table 3. Ordinary Least Squares Regression Results for Resource Productivity, EU-27, 2024

Term	M1	M2	M3	M4
AI_pct	0.0789	-0.0342	-0.0646	0.0646
	(p=0.177)	(p=0.184)	(p=0.063)	(p=0.384)
CMU_pct	0.1016	0.1077	0.0637	0.0790
	(p=0.004)	(p<0.001)	(p=0.352)	(p=0.446)
INV_pctGDP	-0.1786	-0.0949	-0.0927	-0.1784
	(p=0.029)	(p=0.110)	(p=0.090)	(p=0.032)
RD_pctGDP	-0.0511	0.2014	0.2381	-0.0352
	(p=0.898)	(p=0.311)	(p=0.259)	(p=0.932)
GDPpc_EUR	—	0.00003494	0.00003573	—
		(p < 0.001)	(p < 0.001)	
AI_x_CMU	—	—	0.0026	0.0013
			(p=0.402)	(p=0.782)
R^2	0.638	0.832	0.841	0.641
Adjusted R^2	0.572	0.792	0.794	0.555
N	27	27	27	27

Note. Dependent variable: RP (€/kg). M1 includes AI, CMU, INV and R&D; M2 adds GDPpc; M3 adds AI × CMU to M2; M4 adds AI × CMU to M1

without GDPpc. Parentheses report HC3-robust p-values from residual-degrees-of-freedom t tests. N = 27 in all models. AI, CMU, INV and R&D are in percentage points; GDPpc is €/person. The interaction uses original percentage-point scales. Statistical significance is assessed at 5%.

The AI × CMU coefficient in M3 is positive but not significant (β = 0.00260, p = 0.402; HC3 95% CI [-0.00373, 0.00892]). In M4, which excludes GDPpc, the interaction remains non-significant (β = 0.00133, p = 0.782). Thus the data do not establish the predicted complementarity. The sign of the AI main effect changes when GDPpc and the interaction are included; in an uncentered interaction model this main coefficient refers to the AI association at CMU = 0 and should not be interpreted as an overall AI effect.

For M3, the conditional AI marginal effect equals -0.06465 + 0.002598 × CMU. At the 10th, 50th, and 90th percentiles of CMU (2.60%, 9.40%, and 20.94%), the estimated effects are -0.0579 (p = 0.064), -0.0402 (p = 0.200), and -0.0102 (p = 0.852) €/kg per one-percentage-point increase in AI adoption. None is significant at 5%. At the median AI adoption rate (11.31%), the conditional CMU effect is 0.0931 €/kg per percentage point (p = 0.016). The positive conditional CMU association does not imply that AI significantly strengthens it.

Diagnostic tests did not reject homoskedasticity in the four specifications: Breusch-Pagan p-values range from 0.406 to 0.811 and White-test p-values from 0.230 to 0.630. However, Jarque-Bera tests reject residual normality for M2 (p = 0.0002) and M3 (p = 0.0016). RESET tests do not reject the examined functional forms at 5%, although their power is limited in a sample of 27. Cook's distance in M3 exceeds the conventional 4/N screening threshold for Estonia (0.264), Italy (0.234), and Luxembourg (0.151). These observations are retained rather than automatically excluded. Across 27 leave-one-country-out re-estimations of M3, the interaction estimate remains positive but is never statistically significant at 5%. The diagnostics therefore support caution rather than a claim of model certainty.

Table 4. Summary of Hypothesis Testing Results

Hypothesis	Coefficient	HC3 p-value	Decision
H1: AI → RP	0.0789	.177	Not supported
H2a: CMU → RP	0.1016	.0043	Supported in M1
H2b: INV → RP	-0.1786	.0285	Not supported
H3: AI × CMU → RP	0.00260	.402	Not supported

Note. H1, H2a, and H2b are evaluated using M1; H3 is evaluated using M3. Statistical significance is assessed at the 5% level. Coefficients represent associations, not causal effects. Source: Authors' calculations based on Eurostat data for 2024.

Multicollinearity was assessed using variance inflation factors (VIFs). The maximum VIF values, excluding the intercept, were 3.07 in M1 and 4.46 in M2, suggesting no severe multicollinearity in the additive specifications. Higher values were observed in the interaction models, with maximum VIFs of 11.99 in M3 and 11.86 in M4, both associated with the AI × CMU interaction term. Circular material use also exhibited elevated VIFs in these models (7.70 and 7.66, respectively). These results indicate substantial collinearity between the interaction term and its constituent variables, potentially increasing standard errors and reducing the precision of individual coefficient estimates. Accordingly, the interaction results are interpreted cautiously, particularly given the small cross-sectional sample.

6. DISCUSSION

The findings provide a qualified picture of the digital and circular transitions. The baseline positive association between circular material use and resource productivity is consistent with the idea that recovering and reusing materials can coexist with greater economic output per unit of material input. Yet the national indicators are not mechanically equivalent: circular material use measures the role of secondary materials, while resource productivity combines economic output and domestic material consumption. The estimated relationship is therefore empirically informative, although it cannot isolate the contribution of individual circular practices.

The absence of a statistically significant AI coefficient cautions against equating enterprise-level technology diffusion with economy-wide resource-efficiency improvements. The AI indicator records whether an enterprise uses at least one technology, not whether that technology targets material flows or whether the implementation is effective. This distinction is compatible with the organizational-readiness literature (Jöhnk et al., 2021). It also leaves open the possibility of time lags, heterogeneous industry effects, and complementary investments that are not observed in the aggregate data. A non-significant coefficient is not proof that AI has no effect; rather, the study does not detect a reliable independent association conditional on the chosen covariates.

The negative investment coefficient in M1 is not evidence that investment damages circular performance. Gross fixed capital formation includes many

asset types and may coincide with material-intensive construction or expansion, especially in economies undergoing capital deepening. It does not distinguish green from conventional investment. The sign and statistical sensitivity of this coefficient therefore reveal the limits of aggregate investment intensity as a proxy for transition-related financing, rather than a causal relationship between investment and resource productivity.

The interaction result is particularly relevant to the paper's original argument. Although the M3 point estimate is positive, its confidence interval includes zero and the marginal-effect pattern is not statistically decisive. The same conclusion holds when GDPpc is omitted and when individual countries are removed. The proposed synergy between AI diffusion and circular material use remains a plausible organizational mechanism, but it is not demonstrated by this EU-27 cross-section. Future work should use sector-level AI applications, circular investment data, and longer observation windows to test the mechanism more directly.

7. IMPLICATIONS AND LIMITATIONS

For policymakers, the results support examining circular material use alongside broader material-efficiency outcomes rather than relying on AI adoption rates as a sufficient indicator of progress. Digitalization policies may need to focus on applications, skills, interoperability, and measurement of resource outcomes. These are interpretations consistent with the empirical limitations, not causal policy-effect estimates. The 2020 EU Circular Economy Action Plan and the Digital Decade policy program provide relevant institutional context for this question (European Commission, 2020; European Parliament & Council of the European Union, 2022).

For finance and investment decision-makers, the evidence suggests that aggregate capital formation cannot stand in for sustainable finance. The model contains no taxonomy-aligned investment, green bonds, sustainability-linked lending, or firm-level financing data. Consequently, this paper does not estimate the impact of green finance on resource productivity, and the title has been narrowed accordingly. Resource productivity is also only one component of economic performance and does not directly measure international competitiveness, profitability, or welfare.

Several limitations constrain generalization. First, the 2024 cross-section is small and cannot identify dynamic responses or country-specific unobserved factors. Second, AI adoption is an extensive-margin indicator and omits intensity, quality, and purpose of use. Third, circular material use is a partial measure of circularity; material trade, composition, and environmental burden

are not fully captured. Fourth, GDPpc shares an output component with RP, motivating models without GDPpc. Fifth, non-normal residuals in the GDP-controlled models, influential countries, possible multicollinearity, and limited statistical power complicate inference. Finally, reverse causality and omitted variables, including industrial structure, institutions, energy prices, and innovation ecosystems-may affect both the regressors and resource productivity. Robust standard errors and sensitivity checks do not resolve these identification problems. The Eurostat enterprise AI indicator covers only recent survey years, limiting opportunities for longer-run evaluation of diffusion effects; results may change as adoption spreads.

8. CONCLUSIONS

This study examined the relationships between artificial intelligence adoption, circular material use, investment intensity, and resource productivity across the 27 European Union Member States using harmonized Eurostat data for 2024. By integrating technological adoption and circular-economy indicators within a common empirical framework, the analysis sought to determine whether AI and circularity are independently associated with resource productivity and whether AI strengthens the relationship between circular material use and resource efficiency.

The findings provide the strongest support for the role of circular material use. Its positive and statistically significant association with resource productivity in the baseline regression suggests that economies with higher circular material use rates tend to generate greater economic value relative to their material consumption, after accounting for the selected explanatory variables. In contrast, although AI adoption was positively correlated with resource productivity, its coefficient was not statistically significant in the baseline model. Thus, the results do not establish that greater AI adoption is independently associated with higher resource productivity across EU Member States. Investment intensity exhibited a statistically significant negative association with resource productivity in the baseline specification, contrary to the initial hypothesis. This finding suggests that aggregate capital formation should not automatically be interpreted as investment in resource-efficient or environmentally sustainable activities. Moreover, the AI-circular material use interaction was positive but statistically insignificant, providing insufficient evidence that AI adoption strengthens the circularity-resource productivity relationship. The marginal-effects analysis and leave-one-country-out robustness checks reinforced this conclusion.

These findings contribute to the discussion on the EU's twin digital and green transition by highlighting the distinction between technological adoption and

measurable resource-efficiency outcomes. From a policy perspective, the results suggest that circular-economy strategies deserve continued attention, while AI-related initiatives should be evaluated according to their actual contribution to material efficiency rather than adoption rates alone. For sustainable finance, the findings underline the importance of distinguishing general capital formation from investments specifically directed toward circular technologies, resource efficiency, and environmental innovation.

Nevertheless, the conclusions are subject to several limitations, including the small cross-sectional sample, potential reverse causality, influential country observations, and the inability of aggregate indicators to capture sectoral differences or the quality of AI implementation. Future research could employ longitudinal and sector-level data, incorporate direct measures of green investment, and examine organizational and institutional conditions through which AI may support circular-economy performance.

Overall, the study finds a positive association between circular material use and resource productivity but does not establish an independent positive AI effect or a significant complementary relationship between AI adoption and circularity. This distinction provides a basis for more targeted research and policy evaluation concerning the contribution of digital technologies to sustainable economic competitiveness in the European Union.

REFERENCES

Bianchini, A., Rossi, J., & Pellegrini, M. (2019). Overcoming the main barriers of circular economy implementation through a new visualization tool for circular business models. *Sustainability*, *11*(23), Article 6614.

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies "Engines of growth"? *Journal of Econometrics*, *65*(1), 83–108.

De Lucia, C., Pazienza, P., & Bartlett, M. (2020). Does good ESG lead to better financial performances by firms? Machine learning and logistic regression models of public enterprises in Europe. *Sustainability*, *12*(13), Article 5317.

European Commission. (2020). *A new Circular Economy Action Plan: For a cleaner and more competitive Europe* (COM(2020) 98 final).

European Parliament & Council of the European Union. (2022). Decision (EU) 2022/2481 establishing the Digital Decade Policy Programme 2030. *Official Journal of the European Union*.

Eurostat. (2024). *Eurostat database: Resource productivity (cei_pc030); circular material use rate (cei_srm030); enterprises using AI technologies (isoc_eb_ai); GDP and main components (nama_10_gdp); GDP per capita (nama_10_pc); gross domestic expenditure on R&D (rd_e_gerdtot)*. https://ec.europa.eu/eurostat/data/database

Helander, H., Petit-Boix, A., Leipold, S., & Bringezu, S. (2019). How to monitor environmental pressures of a circular economy: An assessment of indicators. *Journal of Industrial Ecology*, *23*, 1278–1291.

Hofmann, F., & Jaeger-Erben, M. (2020). Organizational transition management of circular business model innovations. *Business Strategy and the Environment*, *29*, 2770–2788.

Hysa, E., Kruja, A., Ur Rehman, N., & Laurenti, R. (2020). Circular economy innovation and environmental sustainability impact on economic growth: An integrated model for sustainable development. *Sustainability*, *12*, 4831.

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, *63*(1), 5–20.

Lindgreen, E. R., Salomone, R., & Reyes, T. (2020). A critical review of academic approaches, methods and tools to assess circular economy at the micro level. *Sustainability*, *12*, 4973.

Shi, G., Ma, Z., Feng, J., Zhu, F., Bai, X., & Gui, B. (2020). The impact of knowledge transfer performance on the artificial intelligence industry innovation network: An empirical study of Chinese firms. *PLOS ONE*, *15*(5), e0232658.

Šverko Grdić, Z., Krstinić Nižić, M., & Rudan, E. (2020). Circular economy concept in the context of economic development in EU countries. *Sustainability*, *12*, 3060.

Truby, J. (2020). Governing artificial intelligence to benefit the UN Sustainable Development Goals. *Sustainable Development*, *28*, 946–959.

Ziolo, M., Filipiak, B. Z., Bąk, I., & Cheba, K. (2019). How to design more sustainable financial systems: The roles of environmental, social, and governance factors in the decision-making process. *Sustainability*, *11*, 5604.