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DOES AI READINESS TRANSLATE INTO MATERIAL CIRCULARITY? ECONOMETRIC EVIDENCE FROM THE EU-27

Mohammed Fouad Gassem
University Centre of Maghnia – Institute of Economic, Commercial and Management Sciences, Algeria
https://orcid.org/0009-0008-9063-5777

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ABSTRACT

This exploratory cross-sectional study examines whether national government artificial intelligence (AI) readiness is associated with realised circular material use across the 27 European Union countries. The analysis combines the 2023 Oxford Insights Government AI Readiness Index, Eurostat circular material use rates (CMUR) for 2019 and 2024, and GDP per capita in purchasing power standards for 2023. We estimate ordinary least squares regressions with HC3 heteroskedasticity-robust inference, complemented by a 2019–2024 change specification, 5,000-resample bootstrap intervals, influence and leave-one-out diagnostics, and an alternative outcome using 2023 CMUR. A 10-point readiness difference is associated with 4.51 percentage points higher 2024 CMUR in the unadjusted model (p = .033). The conditional coefficient is −0.505 (95% CI [−2.468, 1.458]; p = .614) after adjustment for 2019 circularity and income. Readiness is also not significantly related to the 2019–2024 change in CMUR. Importantly, Eurostat flags 26 of the 27 CMUR 2024 country observations as imputed, while Luxembourg (10.7%) has no observation-level flag in the current official response; the adjusted result also persists with 2023 CMUR, for which no observation-level status flags appear in the inspected release. The results do not identify causal effects of AI adoption. Instead, they illustrate the limits of interpreting national technological readiness as evidence of realised material-system change.

1 INTRODUCTION

Circular-economy strategies aim to reduce reliance on primary resources by recovering valuable secondary inputs and keeping materials in productive use. The European Union has promoted circularity through policy instruments designed to strengthen resource efficiency, recycling markets and product information (European Commission, 2020). Meanwhile, artificial intelligence (AI) has moved into industrial decision support, enabling pattern recognition, predictive maintenance, materials classification and the optimisation of complex recovery networks. The complementarity is appealing:

Address of the corresponding author:
Mohammed Fouad Gassem
m.gassem@cu-maghnia.dz

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information-intensive technologies may improve the coordination of physical material loops. Yet a technically feasible application is not equivalent to an observed economy-wide circularity gain.

This distinction becomes especially important when digitalisation is measured by national readiness rather than actual deployment. Oxford Insights (2023) measures the capacity of public institutions, technology ecosystems and data infrastructure to support AI uptake. It does not record whether a recycling plant deploys machine vision, whether firms digitally trace secondary inputs, or what quantity of material is recovered because of AI. Material circularity, in contrast, is a realised system-level outcome shaped by cumulative industrial capacity, collection networks, material prices, legislation and patterns of production. A country may score well on the former while exhibiting modest outcomes on the latter.

The present paper asks a deliberately narrower question than whether AI technologies are effective: across the EU-27, is the 2023 national Government AI Readiness Index associated with the 2024 circular material use rate after accounting for countries' 2019 circularity and their 2023 income? The study also examines whether readiness covaries with the absolute change in circularity between 2019 and 2024. The design uses the full set of EU member countries rather than a selected sample, although 27 units necessarily constrain the precision and generalisability of statistical inference.

The paper contributes in three bounded ways. First, it directly links one national AI readiness indicator to a harmonised material-outcome measure, extending a literature centred on digital applications and broad environmental profiles. Second, it separates an unadjusted cross-country gradient from a conditional comparison of countries with similar inherited circularity levels, thereby asking whether readiness contains incremental descriptive information. Third, it makes the measurement and identification limitations explicit, including a country-level replication file and the imputation flags attached to Eurostat's 2024 outcomes. The paper neither tests sector-specific deployment mechanisms nor identifies a causal treatment effect.

The empirical results provide a useful caution. A positive unadjusted readiness–circularity relationship is detectable, but the conditional AI coefficient is small and imprecisely estimated once 2019 circularity is introduced. The same general pattern appears with the 2023 circularity measure, for which no observation-status flags appear in the inspected Eurostat release. This finding cannot prove that AI adoption has no effect; it indicates that a broad readiness ranking does not explain additional national circular-material use in the adjusted cross-section considered here.

2 LITERATURE REVIEW AND HYPOTHESES

2.1 Circularity as a system-level outcome

The circular economy incorporates a portfolio of strategies for narrowing, slowing and closing resource loops; its meaning extends beyond recycling alone (Geissdoerfer et al., 2017; Kirchherr et al., 2017). Physical material balances, however, provide one observable manifestation of loop-closing. Eurostat's CMUR is the share of overall material use supplied through material recycling, calculated using economy-wide material flow information and waste recovery statistics (Eurostat, 2025). The measure is harmonised across member states but does not observe reuse, repair, product-life extension or value retention directly. The interpretation of a high CMUR should therefore remain specific to material recirculation, rather than implying a comprehensive circular-economy ranking.

At the macroeconomic level, installed capital and sectoral composition provide persistence: recycling infrastructure and secondary-material markets accumulate over long horizons and cannot respond instantly to a change in a national technology indicator. Korhonen et al. (2018) additionally emphasise physical system boundaries, rebound effects and governance conditions that constrain idealised circularity narratives. Recent European evidence similarly identifies manufacturing structure, investment, employment and trade as relevant for circular outcomes (Galbreath et al., 2026). Consequently, a one-year material-use level should not be interpreted without considering the country's

position before the acceleration of recent AI deployment.

2.2 Potential AI–circularity pathways and their limits

Digital technologies can support circular strategies by linking sensing, traceability, modelling and coordination to recovery decisions (Kristoffersen et al., 2020; Liu et al., 2022). AI models may improve materials sorting, forecast waste streams, schedule preventative maintenance and optimise reverse logistics. Reviews of AI applications to circular manufacturing and waste management document promising operational use cases, while also describing gaps in data quality, adoption costs, interoperability and institutional integration (Acerbi et al., 2021; Agrawal et al., 2022; Kaigugu et al., 2026). These mechanisms operate initially within firms, facilities or supply chains and do not necessarily translate into higher national material recirculation within a single year.

The Government AI Readiness Index contains governance, technology-sector and data/infrastructure components. Although these dimensions may facilitate environmental information systems and adoption capacity, the score is neither a measure of AI usage in a particular industry nor an estimate of the recycled material generated by AI. The distinction between a potential enabling environment and realised adoption is fundamental. A non-significant relationship with CMUR would not invalidate micro-level AI applications; it would instead limit what can be inferred from a country-level preparedness index.

2.3 Macro-level research gap and hypotheses

Gil-Lamata et al. (2024) show that broader digitalisation dimensions relate to the circular-economy profiles of EU countries, but this evidence does not isolate the Oxford Insights AI score in a regression controlling for past CMUR. The present study therefore evaluates two nested propositions. The first concerns the observed cross-sectional pattern; the second concerns whether readiness retains additional explanatory content conditional on past circularity and income. Neither hypothesis is formulated as a causal claim.

H1: Countries with higher 2023 national AI readiness have higher 2024 circular material use rates in an unadjusted cross-sectional comparison.

H2: National AI readiness retains a positive association with 2024 circular material use after conditioning on 2019 circularity and 2023 GDP per capita.

3 DATA AND ECONOMETRIC METHODS

3.1 Population, measures, years and provenance

The population comprises all 27 EU member states, each observed once; N = 27 throughout. Three sources are combined by Eurostat country code / ISO3 country identifier: Oxford Insights' 2023 Government AI Readiness Index, Eurostat sdg_12_41 (derived from env_ac_cur) for 2019, 2023 and 2024 CMUR, and Eurostat tec00114 (derived from prc_ppp_ind_1) for the 2023 GDP-per-capita PPS volume index (EU27 = 100). All records are present, leaving no missing country observations or imputation performed by the authors. The score is scaled 0–100, CMUR is in percent (and year-to-year differences in percentage points), while income is included as the natural log of its positive index value.

The source values were transcribed and re-estimated on 10 October 2026. A country-level numeric reconciliation against Eurostat was recorded on 17 October 2026, but the publisher's original JSON response was not archived. A subsequent check of the official Eurostat JSON-stat response on 19 October 2026 clarified Luxembourg's 2024 flag (no status entry). The Eurostat CMUR service reported an update of 24 November 2025, and the GDP/PPS indicator a 9 July 2026 update. AI scores were checked against the Oxford Insights 2023 edition as displayed with Oxford Insights attribution by Nations Inquiry; both the original source link and the extracted score provenance are supplied in the reproduction package. Eurostat's published 2024 series has a critical qualification: 26 of the 27 EU-country CMUR records carry the official status flag "i" (imputed), while the Luxembourg value (10.7%) has no observation-level status entry in the Eurostat response inspected on 19 October 2026.

These are official disseminated values rather than fabricated or unreported outcomes, but the flag can matter for inference because sampling-based HC3 standard errors do not incorporate uncertainty in the creation of estimated statistical observations. We therefore report 2023 CMUR, which has no observation-status flags in the inspected official release, as an outcome-vintage sensitivity check. The absence of 2023 flags is not proof that those data are free from estimation or future revision uncertainty.

The 2019 baseline predates the Commission's 2020 Circular Economy Action Plan and the recent generative-AI diffusion wave, offering an interpretable pre-period anchor. Nevertheless, the 2023 readiness measure is observed after much of the 2019–2024 change window; its association with five-year changes should not be interpreted as a forward-looking prediction or a treatment effect. Because Oxford Insights index methods differ across annual editions, the study avoids pooling annual AI scores into an unharmonised panel. Archived source vintages and access dates matter: subsequent revisions may alter the results, and the published spreadsheet enables the estimates to be rerun.

Table 1. *Variables and source definitions*

Variable	Operationalisation	Source and qualification
CMUR 2024	Circular recycled-material share in overall material use (%)	Eurostat sdg_12_41; 2024 "i" flags in 26 states, no flag for LU (19 Oct 2026)
AI readiness 2023	Government AI Readiness Index overall score, 0–100; divided by 10 in regressions	Oxford Insights (2023); readiness, not adoption
CMUR 2019	Baseline circular-material use (%)	Eurostat sdg_12_41; previous level
GDP PPS 2023	GDP per capita PPS real-expenditure volume index, EU27 = 100; natural log	Eurostat tec00114; provisional flags in DE, EL and ES
ΔCMUR 2019–2024	CMUR 2024 minus CMUR 2019 (percentage points)	Calculated difference; 2024 imputation qualification
CMUR 2023	Earlier official CMUR vintage used as sensitivity outcome (%)	Eurostat sdg_12_41; avoid 2024 "i" outcome flags

Source: Authors' elaboration.

3.2 Model sequence and interpretation

The core model in cross-section i is:

$$CMUR(i,2024) = \alpha + \beta\,[AI(i,2023)/10] + \gamma\,CMUR(i,2019) + \delta\,ln(GDP_PPS(i,2023)) + \varepsilon(i).$$

The two-variable model retains only AI readiness; successive models add income, baseline circularity, and both controls. Reporting the nested specifications makes explicit how conditioning changes the relationship. β is measured in CMUR percentage points per ten AI-readiness score points. The estimates are partial correlations after linear projection, not causal effects, because readiness is not randomly assigned and unobserved country structures can jointly shape both measures.

The companion change specification is

$$\Delta CMUR(i,2019–2024) = a + b\,[AI(i,2023)/10] + d\,ln(GDP_PPS(i,2023)) + u(i).$$

A second change specification adds baseline CMUR. The latter is algebraically the same as the fully adjusted levels regression with the coefficient on the baseline reduced by one:

$$\Delta CMUR = \alpha + \beta\,AI/10 + (\gamma-1)\,CMUR2019 + \delta\,\ln GDP + \varepsilon.$$

Thus, it must not be represented as independent confirmation. The model without the baseline control is the separate, complementary change diagnostic, albeit still observational and temporally descriptive.

With only 27 observations, every regression uses heteroskedasticity-consistent HC3 covariance estimates (MacKinnon & White, 1985). The principal p-values and intervals use asymptotic normal inference, matching the original submitted manuscript; an additional Student-t reference with

residual degrees of freedom is provided as a more conservative small-N sensitivity check. Neither convention resolves omitted-variable bias or the fundamental sample-size limit. The preferred inference emphasises estimated coefficient sizes and 95% confidence intervals, not binary significance decisions.

3.3 Diagnostic and robustness procedures

We reproduce Pearson and Spearman correlations, a 5,000-draw country-resampling percentile bootstrap with fixed random seed 20261010, HC3 influence diagnostics, Cook's distance, variance inflation factors, Breusch–Pagan and Jarque–Bera diagnostics, and 27 leave-one-country-out fits. Bootstrap percentile intervals reflect the empirical resampling distribution and should not be treated as a cure for a 27-unit sample. The influence screen uses 4/N (= 0.148) as a flag for closer examination, not a deletion rule; observations are retained in the primary analyses. Variance-inflation values diagnose linear collinearity, while residual normality and heteroskedasticity tests have limited power at this N.

As an outcome-quality sensitivity check, we replace CMUR 2024 by CMUR 2023, which had no per-observation status flags in the inspected release and examine the change from 2019 to 2023. This is not a causal robustness exercise: AI readiness and the alternative 2023 outcome are contemporaneous. No instrumental variable, quasi-experiment, industry-level treatment or direct adoption measure is available. We intentionally avoid adding a large set of country controls or an exploratory interaction without adequate degrees of freedom. The remaining omitted-variable risk is considered a major limitation rather than assumed away by income.

4 RESULTS

4.1 Descriptive statistics

Table 2 summarises the 27-country cross-section. Readiness averages 65.98 (SD 7.15), while mean CMUR increases from 9.09% in 2019 to 10.92% in the official 2024 series; the mean five-year change is 1.83 percentage points. Heterogeneity is substantial: Romania's official 2024 CMUR is 1.3%, compared with 32.7% in the Netherlands. The 2019–2024 change ranges from −3.1 to 6.1 percentage points. Eurostat flags 26 of the 27 country-level CMUR observations for 2024 as imputed; Luxembourg is unflagged in the inspected response. A missing status flag does not by itself demonstrate that an observation is free from estimation uncertainty.

Table 2. EU-27 summary statistics (N = 27)

Variable	Mean	SD	Min.	Median	Max.
AI readiness 2023	65.98	7.15	49.34	67.28	77.36
CMUR 2019 (%)	9.09	6.23	1.40	8.30	26.9
CMUR 2024 (%)	10.92	7.63	1.30	9.40	32.7
CMUR change (pp)	1.83	2.23	-3.10	1.80	6.10
GDP PPS index 2023	103.55	42.0	63	91	248

Note. Authors' calculations from source-transcribed Eurostat and Oxford Insights observations; SD denotes sample standard deviation. In the official response inspected on 19 October 2026, 26 EU-country CMUR observations for 2024 are flagged "i"; Luxembourg has no observation-level status entry.

Authors' calculations

4.2 Bivariate associations

The Pearson correlation between 2023 AI readiness and 2024 CMUR is 0.422 (two-sided p = .028), while Spearman's rank coefficient is 0.400 (p = .039). The unadjusted HC3 slope is 4.509 percentage points for a 10-point readiness difference (SE 2.113; 95% CI [0.368, 8.650]; p = .033). It explains 17.8% of the cross-country variation. These are descriptive, unadjusted cross-sectional results, consistent with H1 but insufficient to infer a readiness-to-circularity conversion channel. The scatter in Figure 1 is wide, including cases such as Finland, with high readiness but low reported CMUR, and the Netherlands, with high values of both.

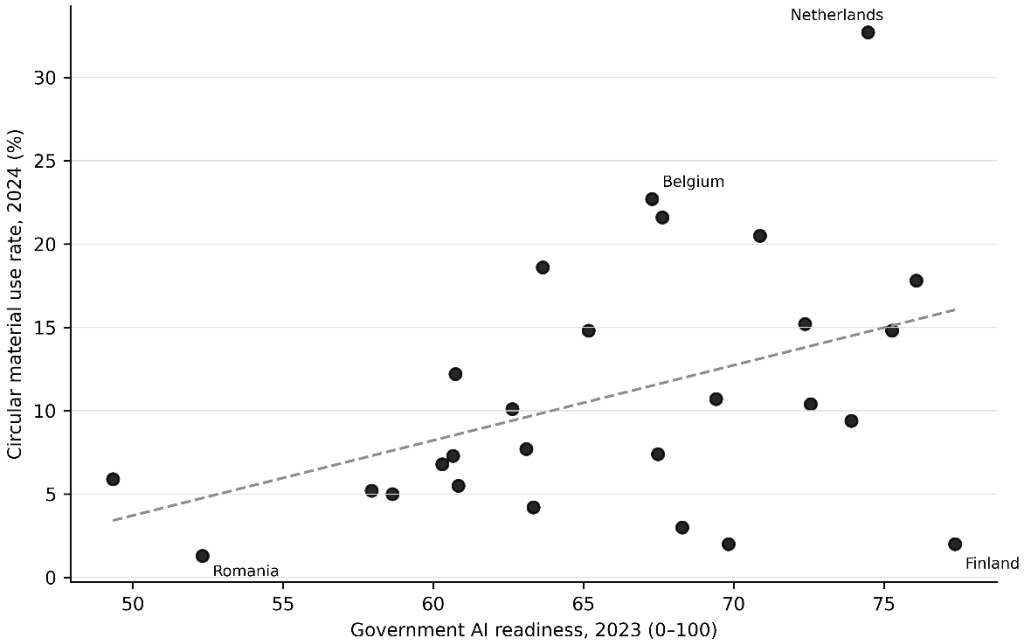


Figure 1. Government AI readiness (2023) and Eurostat CMUR (2024) for the EU-27. Authors' calculations; 26 of the 27 country-level 2024 CMUR observations flagged "i" in the inspected Eurostat response; Luxembourg has no entry.

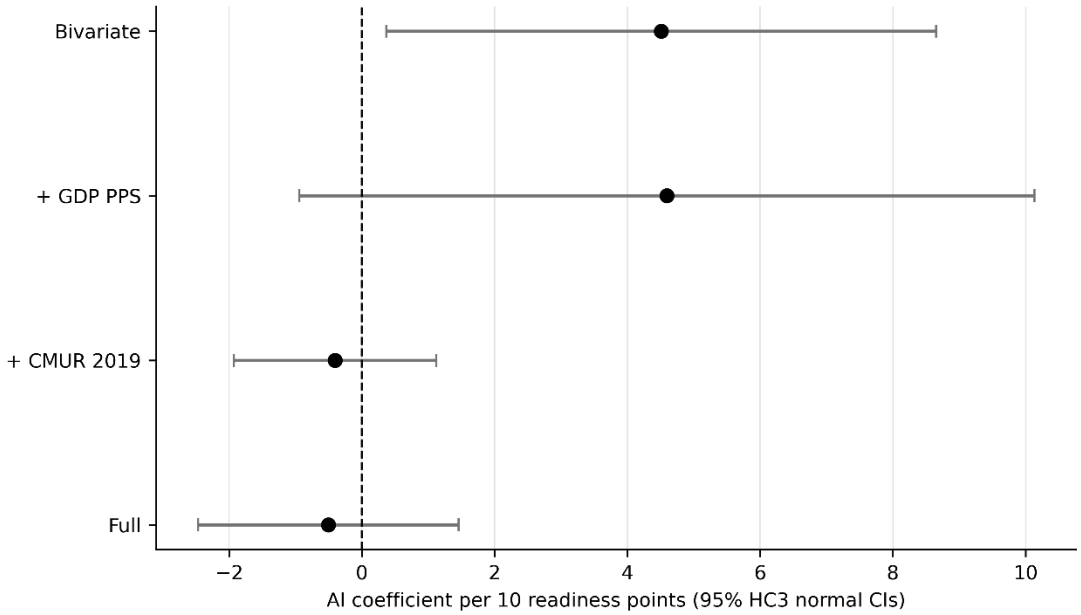


Figure 2. AI-readiness point estimates and 95% HC3 normal-approximation confidence intervals across nested models.

Authors' own calculations

4.3 Conditional Results and the Explanatory Role of Baseline Circularity

Table 3 reproduces four models from the underlying published country data, with differences of roughly 0.001 in some coefficients relative to the submitted table attributable to rounded display values. Income adjustment alone does not eliminate the large positive coefficient but widens its confidence interval; β = 4.594, p = .104. Adding 2019 CMUR changes the estimated AI slope to −0.404 (p = .604). The fully adjusted slope is −0.505 (HC3 SE 1.002; 95% CI [−2.468, 1.458]; p = .614), statistically indistinguishable from zero. Baseline CMUR is strongly associated with 2024 CMUR (β = 1.209), but this reflects persistent material systems and potentially persistent omitted country characteristics, rather than a causal effect of the previous outcome.

Table 3. *OLS models of CMUR 2024; HC3 normal-inference SE in parentheses*

Regressor	(1) Bivariate	(2) + GDP	(3) + CMUR 2019	(4) Full
AI readiness / 10	4.509 (2.113)	4.594 (2.825)	-0.403 (0.777)	-0.505 (1.002)
CMUR 2019	—	—	1.208 (0.075)	1.209 (0.078)
ln GDP per capita PPS	—	-0.334 (6.941)	—	0.392 (1.148)
Constant	-18.832 (13.043)	-17.857 (23.842)	2.606 (4.509)	1.473 (3.868)
N	27	27	27	27
R^2	0.178	0.179	0.939	0.939
Adjusted R^2	0.146	0.110	0.934	0.931

Note: p-values use HC3 normal reference. For AI: M1 p=.033, M2 p=.104, M3 p=.604, M4 p=.614. Percentage-point interpretation applies per ten readiness-score points.

Authors' calculations

The full specification has R^2 = .939, but a regression containing baseline CMUR and income without AI already has R^2 = .938; adding AI increases R^2 by only approximately .0013. This small incremental descriptive fit reinforces the interpretation of a null conditional relationship; a high R^2 is not evidence of causal identification. The wide 95% interval rules out neither all positive nor all negative associations of policy-relevant magnitude. H2 is therefore not supported by these data, not disproved in the logical sense.

4.4 Change models and outcome-year sensitivity

Table 4 reports the complete 2019–2024 change models requested in the review. Without baseline CMUR as a regressor, the coefficient for AI readiness is 0.375 (SE 0.950, p = .693, 95% CI [−1.488, 2.238]; R^2 = .021), providing no clear evidence that readier countries achieved larger CMUR gains.

Table 4. Change in CMUR, 2019–2024 (percentage points), HC3 inference

Regressor / statistic	(D1) ΔCMUR ~ AI + GDP	(D2) + 2019 CMUR
AI readiness / 10	0.375 (SE 0.950); p=0.693; 95% CI [-1.488, 2.238]	-0.505 (SE 1.002); p=0.614; 95% CI [-2.468, 1.458]
CMUR 2019	—	0.209 (SE 0.078); p=0.007; 95% CI [0.056, 0.361]
ln GDP per capita PPS	0.267 (SE 1.767); p=0.880; 95% CI [-3.196, 3.730]	0.392 (SE 1.148); p=0.733; 95% CI [-1.859, 2.642]
Constant	-1.862 (SE 5.493); p=0.735; 95% CI [-12.629, 8.905]	1.473 (SE 3.868); p=0.703; 95% CI [-6.109, 9.055]
N	27	27
R^2	0.021	0.285
Adj. R^2	-0.061	0.192
AI 95% CI lower	-1.488	-2.468
AI 95% CI upper	2.238	1.458

Note. HC3 SE in parentheses. D2 is exactly the baseline-controlled reparameterisation of the M4 levels specification.

Authors' calculations

Adding baseline CMUR yields the mathematically equivalent parameterisation of the full levels regression: the AI coefficient remains −0.505, income remains 0.392, and baseline CMUR becomes 0.209 rather than 1.209. The adjusted change model's R^2 differs because its dependent variable differs, but its unchanged AI coefficient cannot constitute an independent test.

Because 26 of 27 country-level 2024 outcome values carry the Eurostat imputation flag, the same conditional levels specification was also estimated using 2023 CMUR, for which no observation-status flags appear in the inspected official Eurostat release. The 2023 full-model AI coefficient is −0.459 (HC3 SE 0.899, 95% CI [−2.221, 1.303], p = .610). The unadjusted 2023 slope is positive (4.416; p = .029), and the simple 2019–2023 change specification again offers no detectable AI association (0.272; p = .748). The descriptive conclusion therefore does not hinge exclusively on Eurostat's 2024 imputed outcome, though the contemporaneous 2023 specification does not overcome endogeneity or provide causal direction.

4.5 Bootstrap, diagnostics and influential observations

The 5,000-resample percentile bootstrap produces an unadjusted AI confidence interval of approximately [0.723, 8.627] and an adjusted-model interval of [−2.214, 1.148]. The adjusted interval again includes zero. The maximum VIF is 1.764, Breusch–Pagan p = .550 and Jarque–Bera p = .741. Non-rejection by the latter diagnostics is not affirmative evidence of ideal residual behaviour in this small sample. Finland has the highest Cook's distance (0.377), exceeding the exploratory screening value 4/27 = 0.148 even though it is below one. Table 5 reports sensitivity summaries, and a separately supplied 27-country file gives the complete leave-one-out coefficients and influence measures.

Table 5. Robustness and diagnostic summary

Diagnostic	Re-estimated result	Interpretation
Pearson / Spearman AI–CMUR 2024	r = .422 (p=.028) / ρ = .400 (p=.039)	Positive unadjusted association
Bootstrap, unadjusted	95% percentile CI [0.723, 8.627]	Unadjusted interval excludes zero
Bootstrap, full	95% percentile CI [−2.214, 1.148]	Conditional interval spans zero
Leave-one-country-out, full	AI β ranges [-0.814, 0.291]	No stable positive conditional slope
Maximum Cook's D	0.377, Finland; 4/N = 0.148	Influence warrants disclosure
Max VIF	1.764	No severe linear multicollinearity
Breusch–Pagan	p = .550	No rejection; HC3 retained
Jarque–Bera	p = .741	No rejection; small N limits power
HC3 small-sample t, full	AI p = .619	No substantive reversal
CMUR 2023 conditional alternative	AI β = −0.459; p = .610	No conditional evidence using 2023 outcome

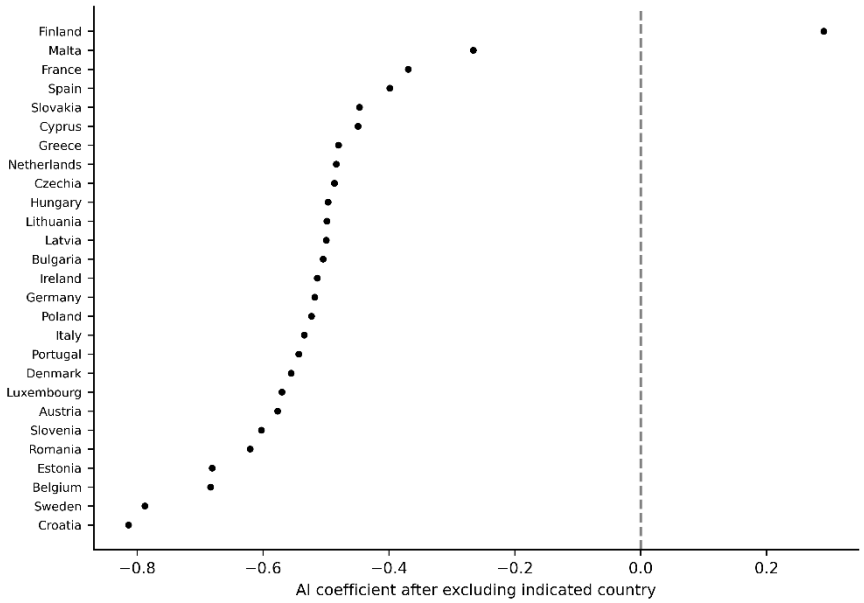


Figure 3. *Leave-one-country-out estimates for the conditional AI coefficient. Dashed line indicates zero; no observation excluded from main results.*
Authors' calculations

5 DISCUSSION AND POLICY IMPLICATIONS

The empirical evidence distinguishes a positive cross-country digital-readiness gradient from the absence of a detectable conditional AI relationship. Countries with relatively advanced institutions and productive structures may perform better on both preparedness and circularity, generating a positive unadjusted association. Yet much of the cross-country difference in 2024 CMUR is already associated with the 2019 circular-material system. The conditional AI coefficient is imprecise, and its small addition to model fit does not support the stronger proposition that national readiness independently converts into measurable additional material recirculation. This inference is descriptive and design-specific.

One interpretation is that public-sector AI readiness lies too far upstream from the industrial practices that enter a material-flow statistic. Operational AI can improve sorting yields, identify product composition and support reverse-logistics decisions, but adoption depends on sector-specific digital investment, quality data, recycling equipment, labour capabilities and demand for secondary materials. Existing systems research and EU evidence make these complements plausible (Kristoffersen et al., 2020; Liu et al., 2022; Galbreath et al., 2026). However, the current regression does not observe these mechanisms, test interactions with them or show that they mediate the AI relationship. Such "catalyst plus substrate" reasoning is therefore a proposed interpretation and research agenda, not an empirical mechanism established here.

There is a second possibility: the 2019 CMUR control captures historically accumulated institutional and infrastructural characteristics that are themselves correlated with later AI readiness. That is precisely why the AI coefficient changes substantially after conditioning, but the change should not be interpreted as proving the absence of an AI effect. It could represent confounding, shared structural history, limited statistical power or attenuation because a composite government index measures the wrong form of exposure for an industrial outcome. Omitting country-specific industrial structure, regulation, materials trade and real AI adoption precludes a causal decomposition of these mechanisms.

For public policy, the disciplined implication is not to abandon AI in circular-economy programmes. Rather, policymakers should distinguish investment in general enabling capacity from measured uptake and material outcomes. Evaluation designs could follow AI deployment in waste sorting, maintenance and reverse logistics, record actual material throughput, assess costs and compare outcomes against credible counterfactuals. Digital product passport information, procurement rules and recycling capacity are potential implementation complements, but their combined efficacy needs direct assessment rather than extrapolation from a cross-sectional readiness coefficient.

6 LIMITATIONS AND FUTURE RESEARCH

Six constraints delimit the inference. First, the full EU-27 population still supplies only 27 country observations, with restricted degrees of freedom and potentially wide uncertainty; HC3, bootstrap and leave-one-out analysis do not enlarge N. Second, the parsimonious specification cannot control comprehensively for industrial mix, waste-management capacity, secondary-material markets, institutional quality, regulation and trade. Income per capita is not a substitute for these factors, and the baseline level may proxy unobserved historical country characteristics. Third, one-year ordering of 2023 readiness and 2024 CMUR does not identify causality, while a 2023 readiness score cannot be treated as a baseline predictor of changes beginning in 2019.

Fourth, the Government AI Readiness Index measures national enabling conditions, not sectoral or enterprise-level AI adoption. Fifth, the CMUR variable represents recycled-material inputs and excludes important circular strategies such as repair and reuse; 26 of the 27 official 2024 member-state values carry the "i" flag in the inspected source response, while Luxembourg does not. HC3 regression standard errors do not account for any measurement uncertainty arising from the underlying statistical estimation. The 2023 outcome sensitivity reduces reliance on the flagged 2024 outcome but does not establish that the unflagged 2023 series is exempt from underlying estimation or revision uncertainties. Sixth, estimates reflect a particular official data vintage; revisions to Eurostat accounts, GDP

purchasing-power comparisons or Oxford Insights indicators may affect coefficients. The companion CSV, code, flags and provenance log are intended to make such differences detectable.

Future studies should exploit harmonised multi-year indicators where measurement editions can be made comparable, collect direct AI deployment and circular-industry investment indicators, differentiate material groups and economic structures, and investigate plausible interactions between AI and installed recycling infrastructure. Where policy timing and treatment data support them, credible quasi-experimental approaches would permit stronger inference than the present cross-section. More granular data could separate public readiness, industrial adoption and actual recycled material supplied to production, allowing the proposed conversion mechanisms to be tested directly.

7 CONCLUSIONS

Across 27 EU member states, 2023 government AI readiness is positively associated with the official 2024 circular material use rate before adjustment. A 10-point difference corresponds to approximately 4.51 percentage points higher CMUR ($p = .033$) in the bivariate comparison. After controlling for 2019 circularity and 2023 income, however, the estimated slope is −0.505 with a 95% confidence interval from −2.468 to 1.458 ($p = .614$). The association is not robust to the introduction of inherited circularity. Neither the simple change model nor the 2023 alternative outcome provides evidence of an additional positive conditional AI association.

These findings do not establish that AI has no impact on the circular economy. The evidence is exploratory, based on national preparedness rather than adoption, and 26 of 27 member-state CMUR 2024 outcomes have the official imputation flag in the inspected response. The results instead caution against equating technology readiness with measured economy-wide recirculation. Establishing whether AI increases circular material flows requires implementation-level measures, complementary system variables, longer comparable time series and a credible research design capable of separating technology deployment from pre-existing national differences.

DATA AVAILABILITY AND REPRODUCIBILITY

Supplementary material contains the 27-country source-transcribed dataset (including 2019, 2023 and 2024 CMUR values; country-specific 2024 Eurostat status flags (including Luxembourg's absent status entry in the 19 October 2026 check) and 2023 GDP provisional flags), the country crosswalk, exact primary source endpoints and retrieval dates, a source-to-result CMUR reconciliation table and executable scripts for numerical replication and API-based verification. The Oxford Insights source is attributed and its redistributed extraction is subject to CC BY-SA 4.0 licensing. The Oxford Insights scores are shown to three decimals, consistent with the 2023 source display; users wishing to reproduce a specific earlier index vintage should compare the attached country values with the publisher's downloadable original file. Source transcription dated 10 October 2026; Eurostat CMUR source release 24 November 2025 and GDP PPS release 9 July 2026. An independent country-level check on 17 October 2026 against the official Eurostat JSON-stat service (sdg_12_41, annual percentage unit) matched all 81 reported CMUR values for the 27 countries in 2019, 2023 and 2024. The 17 October audit transcription recorded "i" for every 2024 country value; however, it did not preserve the original Eurostat JSON response. Direct inspection of the official response on 19 October 2026 shows "i" for 26 of the 27 countries, but no status entry for Luxembourg (LU, 2024 value 10.7%, JSON-stat key 398). No 2023 country value has an observation-level status entry in that response. We cannot establish from the unarchived earlier record whether the Luxembourg discrepancy reflects a publisher revision or a transcription error. Absence of a 2023 status entry does not establish that the statistical inputs are free of estimation or revision uncertainty. The accompanying country-level reconciliation file records each source key and original service URL. The original Eurostat API response was not archived with the 17 October 2026 comparison; a retrieval script is supplied to download and archive the live publisher response for an independently repeatable check. Eurostat may revise the live series.

Replication and verification materials are available from the author upon reasonable request.

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