ISSN 2055-0286
Advances in Social Sciences Research Journal; Vol. 13 No. 11 (2026) (318-335)
https://doi.org/10.14738/assrj.1311.12697

Digitalization, Resource Efficiency, Renewable Energy, and SDG Performance in Mena Countries: A Comparison of GCC and Non-GCC Economies

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Abstract: This study compares the conditional associations of digitalization, resource efficiency, and renewable energy integration with sustainable-development performance in six GCC and six selected non-GCC MENA countries during 2010–2021. All 144 archived SDG Index values match the official backdated series. On the same 132 country-years, the estimated digitalization slope difference between the two groups is 5.583 (95% CI 2.777–8.389) in the dynamic fixed-effects model and 8.438 (95% CI 4.754–12.123) in the static model. The GCC slope is positive and the selected non-GCC slope is imprecise in both specifications. The slope difference also persists after removing three overlapping or related indicators (6.058) and after excluding Goals 7 and 9 (6.316). In contrast, the common-slope dynamic estimate for digitalization is sensitive to covariance bandwidth and country omission, and its sign reverses in an unstable split-panel diagnostic. The renewable-energy slope difference is sensitive to inclusion of the lagged outcome, and the resource-efficiency results depend on index composition. The PCA score places a negative weight on resource productivity, which limits its interpretation as an efficiency measure. The confidence intervals use Driscoll–Kraay standard errors and an approximate time-based t reference. The findings describe within-country associations in a short panel and support a cautious comparison of the two groups.

Keywords: digitalization, resource efficiency, renewable energy, SDG Index, GCC, MENA, dynamic panel, Driscoll–Kraay.

INTRODUCTION

The Middle East and North Africa (MENA) has not followed a uniform path toward the Sustainable Development Goals. In the six Gulf Cooperation Council (GCC) economies, large-scale investment in digital systems and physical infrastructure has proceeded alongside continued dependence on hydrocarbons and resource-intensive production and consumption. The non-GCC countries included here operate under a different mix of constraints, including narrower fiscal space, uneven institutional capacity, and, in several cases, greater political and macroeconomic instability. Yet the contrast cannot be reduced to oil exporters versus oil importers. Algeria and Iran, for example, are important hydrocarbon producers but do not share the GCC's fiscal institutions, policy coordination, or infrastructure profile. GCC membership may therefore capture differences in the capacity to turn transition-related investment into broader development outcomes, rather than differences in resource endowment alone.

The regional literature generally links digital development to better economic and institutional outcomes, although it does not point to a single mechanism. Habibi and Zabardast [15] reported that information and communication technologies were associated

with growth in both Middle Eastern and OECD economies, but also showed that education matters for the return to digitalization. Dhaoui [16] connected e-government with governance and socioeconomic development in a sample of 15 MENA countries. More recently, Mohammed and Laib [17] found positive growth effects from internet access, ICT investment, and digital skills, while noting that fragile states are less able to diffuse these gains. Asmyatullin and Glavina [18] reached a similarly positive conclusion for the GCC in relation to sustainable development. Taken together, these studies justify closer attention to digital capacity, but they do not imply that expanded connectivity translates automatically into comparable social and environmental gains across countries.

The environmental implications of digitalization are less straightforward. Digital systems can improve public-service delivery, make material flows more traceable, coordinate transport, and facilitate smart-grid management. They also require electricity, devices, network infrastructure, and frequent equipment replacement. Goel et al. [5] frame this duality in terms of opportunities and threats, whereas Lange et al. [19] conclude that, to date, the energy-increasing effects of digitalization have outweighed efficiency improvements and sectoral shifts. This evidence cautions against treating digitalization as inherently sustainable. Its net contribution is likely to depend on the energy mix, regulatory choices, user capabilities, and the purposes for which digital infrastructure is deployed.

Circular-economy research raises a different set of measurement and interpretation issues. Schroeder et al. [6] linked a range of circular practices to several SDGs, but conceptual alignment does not necessarily translate into an observable country-level effect. Kirchherr et al. [20] showed that many definitions of the circular economy give considerable weight to recycling and economic prosperity while paying less attention to systemic transformation and social equity. Niero and Kalbar [7] likewise demonstrated that material-circularity indicators and life-cycle indicators capture different dimensions of performance. Korhonen et al. [21] further cautioned that rebound effects, thermodynamic constraints, and displaced environmental burdens can erode apparent gains. These concerns are especially relevant in MENA, where comparable annual data on recycling and recovery are limited. Resource productivity is therefore useful as an empirical proxy, but it cannot be interpreted as a direct measure of closed material loops.

Evidence on renewable energy is similarly conditional on the wider institutional setting. Belaïd et al. [22] found that political stability, financial development, and governance quality shape renewable-energy deployment across MENA economies, with effects that vary across the distribution. Awijen et al. [23] showed that innovation strengthens the influence of governance on renewable deployment. Both studies help explain why renewable capacity can expand more rapidly where finance, regulation, and technology are coordinated effectively. Their findings do not, however, imply that a rising renewable share will immediately be reflected in a broad SDG index. Long project lead times, continued fossil-fuel subsidies, and the fact that energy indicators account for only one part of multidimensional sustainable development may weaken the short-run relationship.

What remains insufficiently resolved is the comparative and dynamic dimension of these transitions. Much of the regional evidence examines digitalization, circularity, and renewable energy separately, and commonly focuses on growth, emissions, or energy deployment rather than overall SDG performance. Cross-country differences are also often

organized around income or resource status, without asking whether a similar within-country change is associated with different outcomes under the GCC institutional setting. This study therefore examines whether digital transformation (DTI), the Resource Efficiency Index (RFEI), and renewable energy integration (REI) move with sustainable-development performance once persistent country characteristics and common year shocks are taken into account. It then tests directly whether the estimated slopes differ between GCC and non-GCC economies.

The analysis addresses three questions: how the transition indices are associated with SDG performance within countries, whether those associations differ between the GCC and the selected comparison economies, and how stable the reported relationships are under alternative measurement and estimation choices. The study reproduces the archived panel estimates and examines their limits through explicit marginal-association calculations, component-level diagnostics, country-influence checks, and a split-panel bias diagnostic. Section 3 describes the data and methods, Section 4 reports the results, and Sections 5 and 6 discuss interpretation and limitations.

THEORETICAL FRAMEWORK AND RELATED LITERATURE

Theoretical Lenses and Analytical Limits

Ecological modernization theory views technological innovation, institutional reform, and cleaner production as potential ways of reconciling economic development with environmental protection [1]. This perspective is relevant here because digital infrastructure can strengthen monitoring and coordination, renewable technologies can alter the composition of energy supply, and more resource-efficient production can reduce material pressure. Its more optimistic interpretation nevertheless requires qualification. Technology produces environmental benefits only when institutions and incentives channel investment toward lower resource use and emissions; otherwise, efficiency improvements may coexist with rising aggregate consumption. For the present analysis, ecological modernization therefore supports a conditional expectation rather than an assumption that modernization is automatically ecological.

Sustainability transition theory places the emphasis less on individual technologies and more on long-run changes in systems of production and consumption [2,3]. Such transitions involve infrastructure, markets, regulation, organizational routines, and user practices, and they typically unfold over extended periods. This perspective helps explain why a digital platform, recycling policy, or solar project may have little immediate association with an aggregate SDG score when complementary institutions have not changed at the same pace. It also gives substantive meaning to persistence: countries inherit grids, skills, administrative capacity, and consumption patterns that cannot be rebuilt from one year to the next.

Innovation diffusion theory provides a further explanation for why similar technologies may produce different outcomes across countries. Adoption depends not only on perceived advantage and compatibility, but also on whether households, firms, and public agencies have the resources and capabilities to finance, understand, and integrate a new practice [4]. Regional evidence supports this qualification. Habibi and Zabardast [15] emphasize education alongside ICT; Mohammed and Laib [17] highlight digital skills and

institutional maturity; and Awijen et al. [23] show that innovation changes the governance–renewables relationship. Thus, comparable technological access need not translate into comparable development outcomes when complementary capabilities differ.

These three perspectives do not require DTI, RFEI, and REI to move together, nor do they imply that the three dimensions should have effects of similar magnitude. Rather, they point to different mechanisms and possible bottlenecks. Digitalization primarily expands information and coordination capacity; resource efficiency concerns the organization and intensity of material use; and renewable integration changes the composition of energy supply. The empirical model therefore estimates their direct conditional associations separately. Interactions with the GCC indicator are then used to assess whether the institutional and fiscal environment associated with GCC membership changes the way each transition dimension relates to SDG performance.

Digital Transformation and Sustainable Development

Digital transformation can support productivity, broaden access to services, improve administrative coordination, and make environmental monitoring more timely. Regional studies generally report favorable economic or governance relationships [15–18], but they differ in what they identify as the key channel. Habibi and Zabardast [15] emphasize education, Dhaoui [16] focuses on e-government, and Mohammed and Laib [17] point to the joint role of infrastructure, skills, and institutions. This broad agreement should not obscure the environmental counterargument. Lange et al. [19] show that direct ICT energy demand and digitalization-induced growth may exceed the efficiency savings generated by digital technologies. Since the dependent variable used in this study combines economic, social, and environmental goals, a positive overall coefficient remains plausible even when some environmental channels are adverse.

- Hypothesis 1: Digital transformation is positively associated with sustainable-development performance across the selected MENA countries.

Resource Efficiency and Sustainable Development

Circular-economy strategies aim to preserve the value of products and materials through prevention, repair, reuse, remanufacturing, and recycling. Schroeder et al. [6] identify links between such practices and several SDGs, particularly those related to industry, responsible consumption, climate, and energy. Yet the concept is not measured uniformly. Kirchherr et al. [20] show that many definitions privilege recycling and economic prosperity over systemic change and social equity, while Niero and Kalbar [7] demonstrate that material-circularity measures and life-cycle environmental indicators answer different questions. Korhonen et al. [21] add that rebound effects and spatial displacement may offset part of the apparent efficiency gain. These considerations motivate a hypothesis about the resource-efficiency dimensions captured by RFEI. The index covers resource productivity, domestic material consumption per capita, and energy intensity. Direct measures of repair, reuse, recycling, and material-loop closure lie outside its scope.

- Hypothesis 2: Greater resource efficiency is positively associated with sustainable-development performance across the selected MENA countries.

Renewable Energy Integration and Sustainable Development

Renewable energy can lower fossil-fuel dependence and emissions, diversify energy supply, and create new investment opportunities. In MENA, however, deployment has been shown to depend heavily on prior institutional and technological conditions. Belaïd et al. [22] identify heterogeneous effects of political stability together with a positive role for financial development, while Awijen et al. [23] report that innovation strengthens the effect of governance quality on renewable deployment. Those studies are concerned primarily with the conditions that enable renewable production to expand. The hypothesis tested here is different: it asks whether renewable integration is associated with a broader SDG outcome. Grid constraints, financing conditions, fossil-fuel pricing, and implementation lags may weaken this association over a relatively short panel even when renewable investment is environmentally beneficial.

- Hypothesis 3: Renewable energy integration is positively associated with sustainable-development performance across the selected MENA countries.

Regional Heterogeneity and Dynamic Persistence

MENA is a particularly useful setting for examining regional heterogeneity because high hydrocarbon dependence coexists with wide differences in fiscal space, political stability, water scarcity, digital readiness, and state capacity. The GCC economies generally combine high levels of connectivity with coordinated national strategies and greater capacity to finance complementary infrastructure [17,18]. The non-GCC group is much less uniform: it includes both energy exporters and import-dependent economies, and several countries have faced tighter financial or political constraints. Evidence on renewable deployment confirms that governance, political stability, finance, and innovation shape transition outcomes within the region [22,23]. Accordingly, a GCC interaction is interpreted here as a difference in within-country slopes associated with this broader institutional setting, not as an oil-versus-non-oil comparison and not as an unconditional ranking of the two groups.

Sustainable-development performance is also expected to display considerable path dependence. Education and health systems, electricity grids, administrative capabilities, and environmental infrastructure accumulate gradually, while current policy operates through assets and institutions inherited from previous years. Including the lagged dependent variable provides a direct way to capture this persistence and reduces the risk of attributing durable development conditions entirely to contemporaneous movements in DTI, RFEI, or REI. At the same time, the coefficient on the lagged outcome must be interpreted with caution because a short dynamic panel can retain finite-sample bias and does not eliminate all sources of endogeneity.

- Hypothesis 4: The associations between the three transition indices and sustainable-development performance differ between GCC and non-GCC countries; the digitalization association is expected to be stronger in GCC countries.
- Hypothesis 5: Sustainable-development performance exhibits positive persistence over time.

MATERIALS AND METHODS

Sample and Data Provenance

The archived workbook covers Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates in the GCC group, and Algeria, Egypt, Iran, Jordan, Morocco, and Tunisia in the selected non-GCC group. There are 12 observations per country over 2010–2021, giving 144 observations. Introducing the one-year outcome lag leaves 132 observations over 2011–2021. The non-GCC sample is a selected comparison group rather than a representative sample of all non-GCC MENA economies.

The dependent variable is sdgi_s in the Backdated SDG Index worksheet of the official SDR 2026 database (database_2026.xlsx) [12,27]. This is the backdated aggregate index, distinct from the 2026 ranking score and the 17-indicator headline progress measure (SDGhi). Merging the archived Panel Data worksheet and the official series by ISO3 code and year matched all 144 scores within 4.98×10^{-11} SDG Index points. The archived values are retained in the main estimates. The official series spans 2000–2025 for every sampled country. The estimation window ends in 2021 because this is the boundary of the archived analytical panel, whose original endpoint rationale is undocumented.

The SDR workbook describes its backdated scores as based on time series with values carried forward in years with missing data. The official comparison verifies the published composite values, while this provider procedure and the archive's own interpolation records remain distinct. The archived workbook identifies ITU/World Bank digital indicators, WGI government effectiveness, material-consumption data from the UN SDG database via Our World in Data, and energy data harmonized by Our World in Data. Original acquisition timestamps and raw pre-interpolation extracts for those archived inputs are unavailable. A fresh WDI audit was retrieved on 5 November 2026 from the release dated 8 October 2026 [26]. Values and metadata from this audit are stored separately and are not silently substituted into the main archived panel.

The archived inflation series is identified as consumer-price inflation through comparison with FP.CPI.TOTL.ZG; it is not GDP-deflator inflation. The archived GDP-per-capita series corresponds to current international dollars rather than a constant-price PPP measure: 105 of 144 observations match the current NY.GDP.PCAP.PP.CD series within 10^{-6}, whereas later revisions account for remaining differences. A constant-2021-international-dollar sensitivity series, NY.GDP.PCAP.PP.KD, was retrieved separately for all 144 observations. The current-price replication has no fixed PPP price base; the sensitivity series explicitly uses the 2021 constant-price basis.

The archived methodology states that internal gaps of at most two consecutive observations were linearly interpolated, without endpoint extrapolation. However, it supplies neither an original missingness mask nor country-variable imputation counts. The fresh WDI audit identifies two missing Saudi fixed-broadband observations, in 2013 and 2014, whose linear interpolation agrees with the archived values within 4×10^{-7} subscriptions per 100 people. These are documented current-source gap candidates, not a verified complete reconstruction of the historical imputation mask. The source-missingness sensitivity checks exclude the two gap rows and, in a separate extended exclusion, also remove the first post-gap Saudi observation in 2015. The original imputation counts for other country-variable combinations remain unverified.

Variables and Index Construction

Table 1: Variable definitions

Variable	Operational measure	Source or status
SDGI	Backdated aggregate SDG Index score (0–100)	SDR 2026, Backdated SDG Index, sdgi_s
DTI	Internet use; fixed broadband and mobile subscriptions per 100 people	ITU via WDI/OWID
RFEI	Resource productivity; reverse-coded DMC per capita and energy intensity	Derived productivity; UN/OWID and energy data
REI	Renewable shares of final energy consumption and electricity generation	UNSD/IEA/IRENA; Ember/Energy Institute via OWID
GOV	Government-effectiveness estimate	WGI 2025 release, as archived
Income	Natural logarithm of GDP per capita, PPP	Current international dollars in replication; constant 2021 dollars in sensitivity
Inflation	Consumer prices, annual percentage change	WDI FP.CPI.TOTL.ZG
Urbanization	Urban population as a percentage of total	WDI SP.URB.TOTL.IN.ZS

For positively oriented component x, normalization is z = (x − min x)/(max x − min x). For adverse components, z = (max x − x)/(max x − min x). Bounds are calculated once over the pooled 144-observation panel; each baseline index is the arithmetic mean of its normalized components. The reconstructed equal-weight indices match the archived indices to within 5×10^{-11}. The normalization bounds are supplied in the replication output. RFEI assigns equal weight to higher resource productivity, lower DMC per capita, and lower energy intensity. The archive and replication outputs retain the original column identifier CEI for this same index.

Resource productivity is a derived variable: archived GDP per capita divided by DMC per capita reproduces it with maximum relative error below 5×10^{-14}. It therefore incorporates income and shares a material-use denominator with the DMC component of RFEI. In the replication, its units are current PPP international dollars per tonne. It is not a direct recycling or material-loop-closure measure. The energy-intensity series is described by the source as primary energy use per unit of GDP; the current corresponding OWID metadata use kilowatt-hours per international dollar [28]. This current metadata check does not establish the archived denominator vintage. REI uses a final-energy share and an electricity-generation share; their denominators must not be treated as interchangeable.

Alternative PCA scores are computed from pooled, favorably oriented components standardized to zero mean and unit population variance. The first principal component is obtained by singular-value decomposition, oriented to correlate positively with the equal-weight average, and rescaled to [0,1]. This sign rule does not ensure positive weights on every component. Section 4.4 reports the eigenvector weights and the variance explained. The resource-use principal component is treated as a separate measurement sensitivity check because its weights have mixed signs.

Estimation and Statistical Inference

The baseline model is $SDGI_{it} = \alpha + \rho SDGI_{i,t-1} + \beta_1 DTI_{it} + \beta_2 RFEI_{it} + \beta_3 REI_{it} + \gamma' W_{it} + \mu_i + \tau_t + \varepsilon_{it}$, where W contains government effectiveness, log income, CPI inflation, and urbanization. Country and year effects are included as explicit indicator variables. The interaction specification adds $\theta_1 DTI_{it} GCC_i + \theta_2 RFEI_{it} GCC_i + \theta_3 REI_{it} GCC_i$. The time-invariant GCC main effect is absorbed by country effects.

All models are estimated by least squares. The replication uses Python 3.12.14, NumPy 2.3.5, pandas 2.2.3, and SciPy 1.17.0; the complete implementation is supplied as reproduce.py. The script constructs the design matrix, estimates its least-squares coefficients, aggregates the score vectors by year, and applies a Bartlett-weighted Driscoll–Kraay covariance estimator [10]. The main bandwidth is two years, with weights $1 - \ell/3$ for lags $\ell = 1,2$. The covariance matrix is multiplied by $n/(n - \text{rank } X)$, matching the archived rounded standard errors.

The tables use a t reference with $T^* - 1$ degrees of freedom, where T^* is the number of estimation years. The reference uses 10 degrees of freedom for the dynamic models and the matched static interaction model and 11 for the full-sample static baseline. Driscoll–Kraay inference relies on a large time dimension [10]. With only 11 estimation years in the matched comparison, the degrees-of-freedom convention and covariance adjustment leave the reported p-values and intervals approximate. The dynamic baseline and interaction designs have ranks 30 and 33 and residual degrees of freedom 102 and 99, respectively. The matched static interaction design has rank 32 and 100 residual degrees of freedom. Each dynamic subgroup model has rank 24 and 42 residual degrees of freedom. Inclusive centered R^2 is $1 - \Sigma e^2/\Sigma(y - \bar{y})^2$ and incorporates the country and year effects.

In the interaction model, β_k is the selected non-GCC slope and $\beta_k + \theta_k$ is the GCC slope. For $a = \beta_k + \theta_k$, $\text{Var}(a) = \text{Var}(\beta_k) + \text{Var}(\theta_k) + 2\text{Cov}(\beta_k, \theta_k)$. Marginal associations and 95% confidence intervals are calculated from this same model and its full covariance matrix. Coefficients from the separate baseline or subgroup models are not combined with the interaction estimates.

Diagnostics and Sensitivity Analyses

The analysis reports the conventional Pesaran CD statistic [11] from the dynamic baseline residuals as an exploratory diagnostic and reports both pooled-regressor VIFs and VIFs after removing country and year effects. Residual first-order correlations are reported by country as descriptive diagnostics. Bandwidths of zero through three, separate group models, and 12 leave-one-country-out estimations assess inference and country influence. The matched static interaction model drops the lagged dependent variable and uses exactly the country-years included in the dynamic interaction model (2011–2021). Both models use the original SDGI outcome, all three interaction terms, the same contemporaneous controls and fixed effects, and the same inference settings. The covariance adjustment uses the rank of each model. RFEI sensitivity checks omit each component in turn and use individual normalized components. Further specifications replace the income control with constant-price PPP income and, separately, also reconstruct resource productivity using that income measure.

An exploratory time split assesses dynamic fixed-effects bias [24,25]. The effective estimation years are divided into 2011–2015 and 2016–2021, retaining the available

precomputed lag at the beginning of each subpanel. With 5 and 6 estimation years, the weighted split-panel diagnostic is bSPJ = 2bFull − (5/11)bFirst − (6/11)bSecond. Its first-order bias cancellation presumes comparable bias terms across the two periods. With such short subpanels, this assumption and estimator stability are demanding; the corrected point estimates are reported as a stress test without attaching unvalidated standard errors. They do not correct regressor endogeneity or establish a preferred causal model.

The SDR 2026 Backdated SDG Index worksheet contains annual normalized indicator scores and goal scores [27]. The mean of the available goal scores reproduces sdgi_s within 2.85×10^{-14} points across the matched panel. Goals 7 and 9 can likewise be recovered as the unweighted means of their four and nine respective normalized indicators. We first recompute Goal 7 without renewable energy in final consumption (n_sdg7_renewcon), and Goal 9 without internet use (n_sdg9_intuse) and mobile broadband subscriptions (n_sdg9_mobuse). Internet use and final-energy renewable share overlap with the concepts used in DTI and REI. Mobile broadband is related to the DTI subscription measures and has a different definition. All other goal scores and the original availability rule are retained. As a broader sensitivity check, we exclude Goals 7 and 9 and average the remaining available goals. The original aggregate averages 17 goals for 96 country-years and 15 for 48. The corresponding counts after goal exclusion are 15 and 13. We recompute the one-year lag separately for each outcome and re-estimate the pooled interaction specification on the same 132 country-years with the original regressors, fixed effects, and inference settings.

EMPIRICAL RESULTS

Descriptive Statistics and Diagnostics

Table 2: Descriptive statistics

Variable	N	Mean	SD	Minimum	Maximum
SDGI	144	64.710	4.571	53.277	72.182
DTI	144	0.431	0.203	0.025	0.943
RFEI	144	0.563	0.115	0.258	0.773
REI	144	0.187	0.260	0.000	0.908
Government effectiveness	144	0.141	0.530	-0.765	1.416
Log PPP income	144	10.198	0.934	8.832	12.106
CPI inflation	144	4.821	7.484	-2.540	43.389
Urban population	144	78.987	16.709	42.449	100.000

The conventional Pesaran CD statistic on the dynamic baseline residuals is −2.232 (nominal normal-reference p = 0.026). Estimated year effects can distort the reference distribution of the residual-based statistic [29]. We therefore treat the statistic and its nominal p-value as exploratory rather than as a formal rejection of zero cross-country residual correlation. Pooled VIFs range from 1.36 to 5.41, with the largest for log income. After removing country and year effects, VIFs for the seven contemporaneous regressors range from 1.12 to 1.39. Country-specific residual lag-one correlations range from −0.651 to 0.709 and are reported as descriptive diagnostics.

Replicated Baseline Models

Table 3: Baseline and alternative specifications

Variable	Dynamic FE	Static FE	PCA dynamic FE
Lagged SDGI	0.752 (0.066)	—	0.756 (0.072)
DTI	2.043 (0.838)	4.668 (1.064)	1.817 (0.604)
RFEI	-0.415 (0.381)	2.581 (1.670)	3.833 (1.335)
REI	0.162 (0.315)	-1.184 (1.146)	-0.106 (0.238)
Government effectiveness	-0.425 (0.374)	-0.487 (0.469)	-0.433 (0.385)
Log PPP income	0.439 (0.355)	-0.116 (0.459)	1.433 (0.512)
CPI inflation	-0.018 (0.013)	-0.027 (0.016)	-0.016 (0.014)
Urban population	-0.085 (0.066)	-0.001 (0.103)	-0.016 (0.071)
Observations	132	144	132
Countries	12	12	12
Residual df	102	114	102
Inclusive R^2	0.988	0.970	0.988

Note: Driscoll–Kraay standard errors with bandwidth two and n/(n − rank X) correction are in parentheses. All columns include country and year effects. Exact p-values and covariance matrices are in the replication package. In the PCA dynamic FE column, the RFEI row refers to the mixed-sign resource-use component described in Table 6.

The reproduced dynamic coefficient on lagged SDGI is 0.752 (SE 0.066), showing substantial descriptive persistence. The baseline DTI coefficient is 2.043 (SE 0.838; revised t-reference p = 0.035). Thus, a 0.1 increase on the normalized digitalization scale is associated with approximately 0.204 contemporaneous SDGI points, holding the included covariates and effects constant. RFEI is −0.415 (p = 0.301) and REI is 0.162 (p = 0.618); neither is precisely estimated. These findings are consistent with H1 under the main reporting convention and with descriptive persistence under H5, but they do not establish stable structural parameters. H2 and H3 are not supported by the baseline estimates. DTI remains positive in the full-sample static baseline (4.668; p = 0.0011) and the reconstructed PCA model (1.817; p = 0.013). These specifications describe contemporaneous associations. The full-sample static baseline also includes 2010, while the comparison in Section 4.8 holds the country-years fixed and evaluates the effect of removing the lag from the interaction specification. High inclusive R^2 reflects the persistent outcome and fixed effects and is not evidence of identification.

Pooled Interactions and Group Marginal Associations

The DTI × GCC coefficient is 5.583 (SE 1.260; t-reference p = 0.0013), representing a slope difference of approximately 0.558 SDGI points per 0.1 DTI increase. In this same model, the

GCC slope is 4.588 (95% CI 2.971–6.205) and the selected non-GCC slope is −0.995 (95% CI −4.090–2.101). The latter is imprecise and should not be interpreted as evidence of a negative digitalization effect. These marginal associations differ from separate-group regressions because the pooled interaction model retains common control coefficients, a common lag coefficient, and common year effects.

Table 4: Pooled interaction model

Term	Coefficient	DK SE	p value	95% CI
Intercept	2.498	15.519	0.875	[-32.079, 37.076]
Lagged SDGI	0.650	0.078	<0.001	[0.477, 0.822]
DTI	-0.995	1.389	0.490	[-4.090, 2.101]
RFEI	-0.581	4.602	0.902	[-10.835, 9.673]
REI	-0.661	0.652	0.335	[-2.114, 0.792]
Government effectiveness	-0.542	0.223	0.035	[-1.039, -0.045]
Log PPP income	1.435	0.412	0.006	[0.517, 2.353]
CPI inflation	-0.013	0.014	0.365	[-0.045, 0.018]
Urban population	0.020	0.107	0.853	[-0.218, 0.259]
DTI × GCC	5.583	1.260	0.001	[2.777, 8.389]
RFEI × GCC	-0.056	4.483	0.990	[-10.045, 9.933]
REI × GCC	0.949	4.322	0.831	[-8.682, 10.579]

Note: n = 132; 12 countries; 11 estimation years; rank X = 33; residual df = 99; inclusive R^2 = 0.9897. Country and year effects are included. Reference country is ARE and reference estimation year is 2011. Their individual coefficients, together with the full 33 × 33 covariance matrix, are exported in the replication files. p-values and intervals use t(10).

Table 5: Group marginal associations from the pooled interaction model

Index	Group	Slope	DK SE	95% CI	p value
DTI	non-GCC	-0.995	1.389	[-4.090, 2.101]	0.490
DTI	GCC	4.588	0.726	[2.971, 6.205]	<0.001
RFEI	non-GCC	-0.581	4.602	[-10.835, 9.673]	0.902
RFEI	GCC	-0.637	0.540	[-1.840, 0.566]	0.266
REI	non-GCC	-0.661	0.652	[-2.114, 0.792]	0.335
REI	GCC	0.288	4.469	[-9.670, 10.246]	0.950

The RFEI and REI interaction estimates are −0.056 (p = 0.990) and 0.949 (p = 0.831), respectively. The corresponding group confidence intervals are wide. Non-significance is not evidence of equal effects, nor does it establish that either transition dimension is unimportant. H4 receives conditional support for a digitalization slope difference under the main specification, with country-influence qualifications described below.

Resource Efficiency and Measurement Sensitivity

The resource-use principal component assigns a weight of −0.588 to resource productivity and positive weights of 0.594 and 0.549 to reverse-coded DMC per capita and energy intensity, respectively (Table 6). Holding the other components constant, higher resource

productivity lowers the PCA score even though it raises the equal-weight Resource Efficiency Index. The positive regression coefficient on this mixed-sign score (3.833, nominal p = 0.017) describes an association with that particular combination of indicators. It cannot substantiate H2, which predicts a positive association for an index that improves when any of its efficiency components improves. PC1 explains 61.27% of the resource-component variance, compared with 69.00% for DTI and 84.11% for REI. The reconstructed PCA scores match the archived scores within 5×10^{-11}.

Table 6: PCA eigenvectors and variance explained

Index	Oriented component	Eigenvector	PC1 variance
DTI	Internet users pct	0.600	69.00%
DTI	Fixed broadband per100	0.559	69.00%
DTI	Mobile subscriptions per100	0.572	69.00%
RFEI	Resource productivity	-0.588	61.27%
RFEI	DMC tonnes per capita	0.594	61.27%
RFEI	Energy intensity	0.549	61.27%
REI	Renewable final energy pct	0.707	84.11%
REI	Renewable electricity pct	0.707	84.11%

Note. Components are min–max normalized, oriented so that higher values represent the favorable direction, and standardized before PCA. The DMC per capita and energy-intensity columns are reverse-coded. PC1 is oriented to correlate positively with the equal-weight average and rescaled to [0,1].

Resource productivity correlates −0.477 with reverse-coded DMC per capita and −0.382 with reverse-coded energy intensity. The correlation between the latter two is 0.397. The main equal-weight RFEI estimate is −0.415 (nominal p = 0.301). When the equal-weight index omits productivity, DMC, and energy intensity in turn, the coefficients are 0.071 (p = 0.919), −0.291 (p = 0.598), and −0.534 (p = 0.031), respectively. Individual-component estimates also vary in sign. The results show sensitivity to index composition and provide limited support for a consistent aggregate association. Full component-level estimates appear in CEI_sensitivity.csv.

Inference Country Influence and Dynamic Bias

Table 7: Bandwidth sensitivity of the digitalization estimates

Model and term	Bandwidth	Coefficient	DK SE	p value
Baseline DTI	0	2.043	1.168	0.111
Baseline DTI	1	2.043	0.880	0.043
Baseline DTI	2	2.043	0.838	0.035
Baseline DTI	3	2.043	0.782	0.026
Interaction DTI × GCC	0	5.583	1.458	0.003
Interaction DTI × GCC	1	5.583	1.455	0.003
Interaction DTI × GCC	2	5.583	1.260	0.001
Interaction DTI × GCC	3	5.583	1.211	<0.001

Changing the bandwidth leaves the common-slope dynamic DTI coefficient at 2.043 but moves its nominal p-value from 0.111 at bandwidth zero to 0.026 at bandwidth three. With 11 estimation years, this range shows why the common slope warrants a cautious interpretation. The DTI × GCC interaction stays positive with nominal $p < 0.01$ at each tested bandwidth. Across leave-one-country-out baseline models, DTI ranges from 0.890 to 3.134. Its nominal p-value exceeds 0.05 when the UAE or Bahrain is omitted. The interaction ranges from 3.719 to 6.402, with $p = 0.068$ when Saudi Arabia is omitted. The replication files report all country exclusions.

Table 8: Exploratory split-panel jackknife diagnostic

Model and term	Full panel	2011–2015	2016–2021	SPJ
baseline L_SDGI	0.752	0.576	0.425	1.010
baseline DTI	2.043	1.551	6.819	-0.339
baseline RFEI	-0.415	-2.029	-1.721	1.030
baseline REI	0.162	-3.987	-0.889	2.622
interaction L_SDGI	0.650	0.480	0.087	1.034
interaction DTI_GCC	5.583	12.616	5.035	2.685
interaction RFEI_GCC	-0.056	12.916	-0.397	-5.766
interaction REI_GCC	0.949	-72.361	12.383	28.034

Note: SPJ = 2 × full − (5/11) × first − (6/11) × second. These are diagnostic point estimates. No valid finite-sample confidence intervals for SPJ are claimed.

The split-panel diagnostic raises the common-slope lag coefficient from 0.752 to 1.010 and reverses the common DTI slope from 2.043 to −0.339. In the interaction model the lag rises from 0.650 to 1.034 and the DTI slope difference falls from 5.583 to 2.685. The REI interaction also varies sharply across subperiods. The short subpanels and the instability across periods limit the diagnostic to a stress test. The sign reversal illustrates sensitivity to this correction, with no calibrated confidence intervals for the corrected estimates. H5 is interpreted as descriptive evidence of persistence in the uncorrected estimates.

Subgroup and Source Related Sensitivity Checks

Table 9: Separate six-country dynamic models

Variable	GCC coefficient and SE	GCC p	Non GCC coefficient and SE	Non GCC p
Lagged SDGI	0.712 (0.101)	<0.001	0.533 (0.111)	<0.001
DTI	5.426 (0.946)	<0.001	1.659 (0.918)	0.101
RFEI	-0.975 (0.499)	0.079	-4.981 (5.144)	0.356
REI	-3.366 (5.445)	0.550	0.487 (0.522)	0.373
Government effectiveness	-1.045 (0.803)	0.222	-0.243 (0.355)	0.510
Log PPP income	2.797 (0.740)	0.004	2.470 (0.741)	0.008

CPI inflation	-0.051 (0.091)	0.587	-0.013 (0.014)	0.400
Urban population	-0.080 (0.185)	0.675	0.063 (0.082)	0.463

Note: Each model uses 66 observations, six countries, 11 estimation years, country and year effects, and residual df = 42. p-values use t(10). These exploratory models allow all included slopes to differ and do not replace the pooled interaction test.

The separate DTI coefficients are 5.426 in GCC economies ($p < 0.001$) and 1.659 in the non-GCC sample ($p = 0.101$ with the revised t reference). These coefficients do not establish a statistically significant group difference by themselves. Replacing the income control with fresh constant-price PPP income yields baseline DTI = 1.945 ($p = 0.038$) and DTI × GCC = 6.157 ($p < 0.001$). Also reconstructing productivity from constant-price income yields baseline DTI = 1.944 ($p = 0.037$) and DTI × GCC = 6.174 ($p = 0.0016$). These checks address price-basis sensitivity but combine archived non-income variables with a later income release; they are not a vintage-matched replacement dataset.

Removing Saudi Arabia's 2013 and 2014 fixed-broadband gap rows leaves 130 observations. The common-slope DTI estimate is 2.011 ($p = 0.040$) and DTI × GCC is 5.534 ($p = 0.0017$). The extended exclusion also removes Saudi Arabia's first post-gap observation, 2015, leaving 129 observations. The estimates are 2.015 ($p = 0.046$) and 5.534 ($p = 0.0018$), respectively. The extended exclusion tests sensitivity to dropping the post-gap observation. Fixed broadband enters the contemporaneous DTI, and the one-year lag is computed from SDGI on the full panel before either exclusion. Both checks use gaps identified in the available WDI snapshot. The original imputation mask remains unavailable.

Sensitivity to Overlap in the Outcome

Table 10: Interaction estimates under alternative SDG Index outcomes

SDG Index outcome	Interaction	Coefficient	95% CI	p value
Official backdated index	DTI × GCC	5.583	[2.777, 8.389]	0.001
	RFEI × GCC	-0.056	[-10.045, 9.933]	0.990
	REI × GCC	0.949	[-8.682, 10.579]	0.831
Three indicators excluded	DTI × GCC	6.058	[3.572, 8.544]	<0.001
	RFEI × GCC	0.226	[-9.598, 10.049]	0.960
	REI × GCC	2.193	[-7.103, 11.490]	0.611
Goals 7 and 9 excluded	DTI × GCC	6.316	[3.702, 8.930]	<0.001
	RFEI × GCC	-2.526	[-11.577, 6.526]	0.548
	REI × GCC	1.398	[-9.871, 12.667]	0.788

Note. All models use 132 observations, country and year fixed effects, and a one-year lag of the outcome in the corresponding row block. Confidence intervals and p-values use bandwidth-two Driscoll–Kraay standard errors with the same covariance correction and t(10) reference as Table 4.

Re-estimating the original model with the official values gives the same coefficients at the reported precision. The DTI × GCC coefficient is 6.058 (95% CI 3.572–8.544) after removing the three indicators and 6.316 (95% CI 3.702–8.930) after omitting Goals 7 and 9. The GCC digitalization slope remains positive in both variants, at 4.297 (95% CI 2.673–5.922)

and 4.112 (95% CI 1.916–6.309), respectively. The corresponding non-GCC slopes are −1.761 (95% CI −4.862 to 1.340) and −2.204 (95% CI −5.673 to 1.265). The wider slope difference therefore accompanies a modest decline in the GCC slope and a more negative, imprecisely estimated comparison slope. The confidence intervals for RFEI and REI interaction terms include zero in both variants.

Static and Dynamic Interactions on the Same Sample

The DTI × GCC interaction is 5.583 in the dynamic model (p = 0.0013) and 8.438 in the static model (p = 0.00046). The estimated GCC slope rises from 4.588 to 7.420 when the lag is omitted, while the non-GCC slope remains near −1 with intervals spanning zero. The comparison holds the estimation sample fixed. The two specifications describe associations with different conditioning sets, so the difference in coefficients does not measure a long-run response or establish which specification is preferable. Across bandwidths zero through three, the DTI interaction has a nominal p-value below 0.01 in both models.

Table 11: Static and dynamic interaction estimates for 2011–2021

Term	Dynamic coef.	95% CI	Static coef.	95% CI
DTI × GCC	5.583	[2.777, 8.389]	8.438	[4.754, 12.123]
DTI slope in GCC	4.588	[2.971, 6.205]	7.420	[4.645, 10.195]
DTI slope in non-GCC	-0.995	[-4.090, 2.101]	-1.018	[-3.575, 1.539]
RFEI × GCC	-0.056	[-10.045, 9.933]	7.692	[-5.952, 21.337]
RFEI slope in GCC	-0.637	[-1.840, 0.566]	1.552	[-1.564, 4.669]
RFEI slope in non-GCC	-0.581	[-10.835, 9.673]	-6.140	[-21.511, 9.231]
REI × GCC	0.949	[-8.682, 10.579]	13.964	[5.037, 22.892]
REI slope in GCC	0.288	[-9.670, 10.246]	12.842	[2.651, 23.033]
REI slope in non-GCC	-0.661	[-2.114, 0.792]	-1.122	[-3.167, 0.923]

Note. Both columns use the same 132 country-years and the same country and year effects, contemporaneous controls, and interactions. The dynamic model also includes the one-year lag of SDGI. Intervals use Driscoll–Kraay standard errors with bandwidth two, the model-specific n/(n − rank X) adjustment, and a t(10) reference.

The RFEI interaction is imprecise in both models. The REI interaction changes from 0.949 in the dynamic model (p = 0.831) to 13.964 in the static model (p = 0.0059). This contrast persists across the four tested bandwidths and shows that the renewable-energy result is especially sensitive to conditioning on the previous SDGI score.

DISCUSSION

The comparison between the GCC and the six selected non-GCC economies is the clearest digitalization result. The estimated slope difference is positive in both models fitted to the same country-years, although its magnitude depends on whether the regression conditions on prior SDG performance. The GCC slope is positive in both models, while the non-GCC slope remains imprecise. The common DTI slope in the pooled baseline summarizes a different specification and is sensitive to the choices described in Section 4.5.

The nominal significance of the common dynamic slope depends on the bandwidth and on which countries enter the sample. The pooled interaction is less sensitive to bandwidth, but omitting Saudi Arabia weakens its nominal significance in the dynamic model. The split-panel diagnostic is unstable, and the short time dimension limits the precision of the covariance estimates. Fiscal capacity, coordinated infrastructure, public-service integration, and complementary skills are plausible mechanisms that the GCC interaction does not identify separately. Reverse causality and omitted time-varying factors remain possible.

The DTI measures access and subscriptions. It does not directly measure the environmental footprint, affordability, or inclusiveness of digital infrastructure. The GCC–non-GCC slope difference persists when the specified connectivity and renewable-energy indicators are removed and when Goals 7 and 9 are omitted altogether. This reduces concern that those particular part–whole links account for the entire slope difference. The checks address measured overlap in the outcome. They leave open the roles of other shared development drivers and changes in country institutions over time.

The resource-efficiency results depend on how the components are combined. Higher productivity raises the equal-weight RFEI but lowers the PCA score when the other components are held fixed. This distinction explains why the positive PCA coefficient does not support H2. Productivity also shares the material-use denominator with DMC per capita and incorporates the income variable mechanically. The estimates therefore warrant cautious interpretation. This distinction between resource use and circularity is consistent with the measurement concerns in Kirchherr et al. [20], Niero and Kalbar [7], and Korhonen et al. [21].

The renewable-energy slope difference is sensitive to the treatment of prior SDG performance. On the same country-years the static interaction is positive, whereas the dynamic estimate is smaller and imprecise. The difference across specifications limits the evidence for a stable renewable-energy association. Starting renewable shares differ across countries, and some projects may take years to affect a broad SDG outcome. Belaïd et al. [22] and Awijen et al. [23] examine factors that influence renewable deployment, a separate outcome from the SDG association estimated here.

Policy interpretation should accordingly remain modest. Digital programs can be evaluated jointly with affordability, public-service access, skills, energy demand, and environmental monitoring. Circular-economy policy needs direct information on repair, reuse, recycling, secondary materials, and waste prevention. Renewable-energy assessments benefit from energy-specific outcomes and investment lags. These are research and evaluation priorities informed by the measurement framework and broader literature; the present regressions do not estimate the effects of particular interventions.

CONCLUSION

In the 12-country sample, the association between digitalization and SDG performance is more positive in GCC economies than in the six selected comparison economies in both pooled interaction models estimated on the same 2011–2021 country-years. Its magnitude depends on conditioning on prior SDG performance. The difference also persists in both outcome overlap checks. The common dynamic digitalization slope is sensitive to bandwidth

and to the split-panel diagnostic. Resource-efficiency associations depend on index composition, and the renewable-energy slope difference depends on whether the model includes the lagged outcome.

Inference is approximate in the short time dimension and the interaction is sensitive to country omission. Current-price PPP measurement, provider carry-forward in the backdated SDGI, source revisions, and incomplete historical imputation records further limit interpretation. The estimates describe conditional associations. Longer panels, vintage-matched source extracts with imputation masks, and direct circularity measures would support stronger inference.

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