

# Modeling Circular Economy Using Industry 5.0 Technologies for Sustainable Engineering Projects: A Serial Mediation Model of Digital-Circular Capability

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## Research Article

**Keywords:** Circular economy, Industry 5.0, digital-circular capability, energy efficiency, cost efficiency, sustainability performance, structural equation modeling, serial mediation

**Posted Date:** October 28th, 2026

**DOI:** <https://doi.org/10.21203/rs.3.rs-11507181/v1>

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**Additional Declarations:** No competing interests reported.

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# Abstract

This study examines how circular economy (CE) practices and Industry 5.0 (I5) technologies translate into sustainability performance (SP) in engineering organizations. Survey data were collected from engineering and technical professionals in Saudi Arabia's energy, manufacturing, construction, and infrastructure sectors; after screening for careless responding, 147 of 159 responses were retained. Exploratory factor analysis showed that CE and I5 items formed a single factor, so they were modeled as one construct, digital-circular capability (DCC). Confirmatory factor analysis supported a 15-item, four-construct measurement model (CFI = 0.926, RMSEA = 0.066, SRMR = 0.070). Structural equation modeling with 2,000 bootstrap resamples showed that DCC improves energy efficiency (EE) ( $\beta = 0.345$ ), EE improves cost efficiency (CEF) ( $\beta = 0.747$ ), and CEF improves SP ( $\beta = 0.503$ ). The serial indirect effect DCC  $\rightarrow$  EE  $\rightarrow$  CEF  $\rightarrow$  SP was significant ( $\beta = 0.130$ ; bootstrap 95% CI of the unstandardized effect [0.021, 0.259]), alongside a direct effect of DCC on SP ( $\beta = 0.439$ ), while DCC had no direct effect on CEF. The model explains 55.9% of the variance in SP, and the results held in the unscreened sample, among core engineering roles only, and with technology-worded SP items removed. The study introduces DCC as an integrated capability and identifies an energy-to-cost pathway through which it supports sustainability. Because the measurement structure was derived and tested on the same sample, the model should be confirmed on independent data.

## 1. Introduction

Engineering organizations face two pressures at once. The first is the demand to use resources more sustainably, which has pushed firms toward circular economy (CE) models that keep materials in use through reduction, reuse, recycling, and recovery [1]. The second is the spread of advanced digital technologies. Industry 5.0 (I5) builds on the technologies of Industry 4.0, such as artificial intelligence (AI), the Internet of Things (IoT), and smart automation, but directs them toward sustainability, human-centricity, and resilience [2], [3].

The two agendas have converged. Systematic reviews show that digital technologies act as enablers of circular strategies [4], [5], and studies in Saudi Arabia report that Industry 4.0 supports the circular and lean practices through which firms improve sustainability [6], [7]. Meta-analytic evidence confirms that CE practices improve both commercial and ecological outcomes [8], [9].

Three gaps remain. First, most studies treat CE and digital technology as separate constructs linked by a path, even though practitioners may experience them as one capability. Second, the operational mechanism through which these capabilities produce sustainability outcomes is rarely modeled explicitly; recent work has begun to test sequential mediation [10], [7], but the roles of energy efficiency (EE) and cost efficiency (CEF) as links in a chain have not been examined. Third, evidence from engineering organizations in the Gulf region, where energy use is a central operating concern, remains limited.

This study addresses these gaps with survey data from 147 engineering and technical professionals in Saudi Arabia. It makes three contributions. First, it shows that CE and I5 items form a single factor and introduces digital-circular capability (DCC) as an integrated construct. Second, it identifies a serial pathway,  $DCC \rightarrow EE \rightarrow CEF \rightarrow SP$ , alongside a direct effect of DCC on sustainability performance (SP). Third, it tests the robustness of this pathway across alternative samples and specifications and reports transparently that the model was re-specified from the data, so that future studies can confirm it.

The remainder of the paper is organized as follows. Section 2 develops the theoretical framework and hypotheses. Section 3 describes the method. Section 4 reports the results. Section 5 discusses the findings, contributions, implications, and limitations, and Section 6 concludes.

## 2. Theoretical Foundations and Hypotheses

### 2.1 Theoretical Lens

The framework draws on three related perspectives, each explaining a different link in the model.

The resource-based view (RBV) holds that firms gain lasting advantage from resources that are valuable, rare, inimitable, and non-substitutable [11]. A capability that combines circular practices with intelligent technologies fits this definition. Each part is widely available, but the combination is firm-specific and hard to copy, because it depends on how practices and systems are tied together in daily operations.

The natural-resource-based view (NRBV) extends RBV by arguing that advantage increasingly rests on a firm's relationship with the natural environment [12]. Its first strategy, pollution prevention, links environmental improvement directly to lower operating costs, because emissions and waste are signs of inefficient resource use [12]. Revisiting the theory fifteen years on, Hart and Dowell [13] called for further work connecting it with dynamic capabilities, that is, with how environmental resources are actually turned into performance. The present study responds by modeling one such pathway explicitly.

Dynamic capabilities theory explains how firms integrate, build, and reconfigure competences to respond to changing environments [14]. Teece [15] separates this into sensing opportunities, seizing them, and transforming the organization, and Eisenhardt and Martin [16] show that such capabilities are identifiable routines rather than abstract potential. In this study, the routines of monitoring energy use, recovering materials, and automating processes are what turn a resource bundle into measurable operational gains.

Recent work has combined these lenses in the same setting. Bag et al. [17] used RBV with institutional theory to show, across 219 manufacturing firms, that resources devoted to AI-powered big data analytics shape circular economy capabilities. Chaudhuri et al. [18] combined RBV with ambidexterity theory and found that small firms build circular and digital capabilities in sequence, exploiting circular resources first and then exploring digital tools. Both studies treat circular and digital capability as intertwined rather than separate, which is the starting point of this framework.

### 2.2 Digital-Circular Capability

The CE replaces the linear take-make-dispose model with practices that reduce, reuse, recycle, and recover materials across production and consumption [1]. I5 builds on the digital technologies of Industry 4.0 but redirects them toward three goals: sustainability, human-centricity, and resilience [3], [2]. Ivanov [19] frames these goals as a viability-based system rather than separate aims, and Leng et al. [20] trace how I5 shifts the purpose of manufacturing technology from efficiency alone to wider societal value. Ghobakhloo et al. [21] set out a strategy roadmap of how I5 functions deliver sustainability values.

A large body of work shows that CE and digital technologies are not independent. Lopes de Sousa Jabbour et al. [22] proposed that Industry 4.0 technologies are what make circular operations feasible at scale. Systematic reviews by Rosa et al. [4] and Chauhan et al. [5] confirm that the two literatures have converged, with digital technologies acting as enablers of circular strategies. Kristoffersen et al. [23] formalized this convergence as the "smart circular economy," a framework in which data and analytics drive each circular strategy.

Empirical work in Saudi Arabia points the same way. Ghaithan et al. [6] surveyed 486 Saudi organizations and found that Industry 4.0 and lean manufacturing act as enablers through which CE improves sustainability performance. Elnadi et al. [7] surveyed 170 Saudi respondents and found that Industry 4.0 drives circular, lean, and agile practices, which in turn mediate its effect on sustainability. Tiwari et al. [10] reported a similar sequential pattern in India, where CE practices mediate the link between Industry 4.0 and sustainable performance.

This study takes the convergence one step further. Prior work treats CE and digital technology as distinct constructs linked by a path. In the present data, practitioners did not distinguish them: the two sets of items formed a single factor (Section 4.1). We therefore define digital-circular capability (DCC) as an organization's joint deployment of circular practices (material recovery and the use of recovered inputs) and intelligent technologies (AI, IoT, and smart automation) as one integrated operational capability. In RBV terms [11], DCC is a resource bundle whose value lies in the combination; in dynamic capability terms [15], it is the routine through which the bundle is put to work.

Two caveats bound this definition. First, it emerged from the data and needs confirmation on an independent sample. Second, the technology items reflect the digital technologies shared by Industry 4.0 and I5; the human-centric and resilience dimensions that distinguish I5 [2], [19] were not measured, so DCC captures the technological core of I5 rather than the full paradigm.

## 2.3 DCC and Energy Efficiency

The most direct operational effect of DCC is on how much energy a process uses. Beltrami et al. [24] identify real-time energy monitoring, smart metering, and optimized production scheduling as the main routes through which Industry 4.0 technologies raise energy efficiency. Ghobakhloo et al. [25], reviewing 745 studies, consolidate the sustainability value drivers of digital transformation, among which resource and energy efficiency feature. Circular practices add to this: for many materials, recovered and recycled

inputs require less energy than virgin ones, and lifecycle thinking draws attention to the energy embedded in each stage.

Firm-level evidence supports the link. Hao et al. [26], using Chinese listed firms from 2010 to 2022, found that enterprise digital technology lowers energy intensity, with the effect strongest in manufacturing. Long et al. [27] found that a national broadband program raised energy efficiency by about 10.5% in coal-using and 11.3% in oil-using firms.

The effect is not automatic. Long et al. [27] also found that energy efficiency fell by about 17.2% in electricity-using firms, and Beltrami et al. [24] warn that data centers, AI, and additive manufacturing can add energy demand. Beccarello and Di Foggia [28] found that Italian manufacturers adopted Industry 4.0 mainly for production optimization and flexibility rather than energy savings. DCC should therefore improve energy efficiency where its tools are aimed at energy use, which the monitoring and automation items in this study capture.

*H1. Digital-circular capability positively affects energy efficiency.*

## **2.4 Energy Efficiency and Cost Efficiency**

Energy is a direct operating cost, so using less of it for the same output lowers cost by definition. The more important question is whether the savings reach beyond the energy bill, and the evidence suggests they do. Worrell et al. [29], reviewing more than 70 industrial case studies, found that energy efficiency measures brought productivity benefits large enough to double the cost-effective efficiency potential in the US iron and steel sector. Cagno et al. [30] organized these non-energy benefits into a framework covering both the implementation and the operating phases of an efficiency measure and validated it with manufacturing firms.

Management practice matters as well. Martin et al. [31], studying UK manufacturing plants, found that climate-friendly management practices were associated with both lower energy intensity and higher total factor productivity. Among Italian manufacturers, Beccarello and Di Foggia [28] found that energy efficiency measures were adopted mainly for cost reduction. NRBV adds the theoretical reason: pollution prevention lowers cost because waste and excess energy use are forms of inefficiency [12].

*H2. Energy efficiency positively affects cost efficiency.*

## **2.5 Cost Efficiency, DCC, and Sustainability Performance**

The traditional view treats environmental effort as a cost that competes with profit. Porter and van der Linde [32] challenged this view, arguing that pollution is a sign of wasted resources and that environmental improvement and competitiveness can rise together. Hart and Ahuja [33] supported the argument empirically, finding that emission reductions were followed by better operating and financial performance. NRBV formalizes the same logic [12].

For H3, the argument runs from cost to sustainability. Cost savings that come from using fewer resources are themselves evidence of a lower environmental load, and they free resources that firms can reinvest in further sustainability measures. They also make sustainability programs defensible internally, which supports the long-term resilience that the SP construct captures. Pan et al. [9], in a meta-analytic structural equation model of 66 studies covering 13,643 manufacturing firms, found that circular practices improve cost, operational, and financial performance alongside environmental outcomes, which is consistent with cost and sustainability gains moving together.

**H3.** *Cost efficiency positively affects sustainability performance.*

DCC should also affect sustainability directly, through routes that do not pass through energy or cost. Recovering materials and using recycled inputs reduce waste and virgin-resource use regardless of their cost effect, and monitoring technologies make environmental performance visible and manageable. Yin et al. [8], in a meta-analysis of 41 studies, found that CE practices improve both commercial and ecological sustainability. Mora-Contreras and Carrillo-Hermosilla [34] examine circular economy, eco-innovation, and Industry 4.0 together as drivers of sustainability performance and competitive advantage in manufacturing companies.

**H4.** *Digital-circular capability positively affects sustainability performance directly.*

One result in Pan et al. [9] sets a boundary: hybrid practices combining several circular principles were associated with lower environmental performance even as they improved cost. A direct DCC–SP link should therefore not be assumed to hold for every type of circular practice.

## 2.6 The Serial Pathway and the Alternative

H1 to H3 together describe a chain: DCC improves energy efficiency, energy efficiency lowers cost, and cost efficiency supports sustainability performance. The chain follows the dynamic capability sequence [15]. DCC is the resource bundle; energy efficiency is the first operational gain it produces; cost efficiency is the economic result that makes the gain durable; and sustainability performance is the outcome. NRBV supplies the logic of each step [12], [13].

Sequential mediation of this kind has precedent in the same literature. Elnadi et al. [7] found that circular, lean, and agile practices mediate the effect of Industry 4.0 on sustainability in Saudi Arabia. Tiwari et al. [10] found a sequential path from Industry 4.0 through organizational and circular factors to sustainable performance. Dev et al. [35] showed through simulation that combining Industry 4.0 with circular strategies produces trade-offs between economic and environmental outcomes, which is why the economic link is modeled explicitly here rather than assumed. A three-path mediated effect of this form can be tested directly [36].

**H5.** *Energy efficiency and cost efficiency serially mediate the effect of digital-circular capability on sustainability performance (DCC → EE → CEF → SP).*

A simpler explanation is that DCC reduces cost directly, without passing through energy efficiency. Predictive maintenance, automation, and material recovery can all lower cost on their own [9]. If that were the main route, the serial chain would be redundant. The model therefore tests the direct path as a competing hypothesis.

**H6 (alternative).** *Digital-circular capability directly affects cost efficiency.*

## 3. Method

### 3.1 Research Design and Data Collection

The study follows a positivist, deductive approach with a cross-sectional survey design. The target population was engineering and technical professionals working in Saudi Arabia's energy, manufacturing, construction, and infrastructure sectors. Respondents were reached through non-probability purposive sampling and completed an online questionnaire between 11 and 28 May 2026. Each respondent reported on practices and outcomes in his or her own organization, acting as a key informant. A total of 159 responses were received.

### 3.2 Measures

The questionnaire contained 20 items intended to measure five constructs with four items each: CE practices, I5 technologies, EE, CEF, and SP. All items used a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). CE items covered waste reduction, recycling and material recovery, lifecycle optimization, and the use of recycled or recovered materials. I5 items covered AI-supported decision-making, IoT-based real-time monitoring, digital twins and smart simulation, and smart automation. EE items covered active energy reduction, the contribution of smart technologies and real-time monitoring to energy efficiency, and sustainable engineering practices. CEF items covered cost reductions from CE practices, intelligent cost management, predictive maintenance, and digital transformation. SP items covered environmental performance, the contribution of intelligent technologies to sustainable operations, long-term operational resilience, and overall sustainability outcomes. The full wording of every item and its final status are given in Appendix A. Demographic variables included gender, age, education, sector, years of experience, and job position.

### 3.3 Data Screening

Of the 159 responses, 12 were excluded, leaving N = 147. Eleven showed straight-lining, giving the identical response to all 20 items (five answered all "agree," five all "strongly agree," and one all "strongly disagree"). Such invariant patterns indicate careless responding and inflate inter-item correlations [37]. One respondent worked in the healthcare sector, outside the target population. There were no missing values. Results on the full sample are reported as a robustness check (Section 4.6).

### 3.4 Sample Profile

Table I summarizes the final sample. Most respondents were male (72.1%), aged 31–40 (52.4%), and held a bachelor's degree (63.9%). The four target sectors were evenly represented, and half of the respondents had 5–10 years of experience.

TABLE I. SAMPLE PROFILE (N = 147)

| Variable   | Category                           | n   | %    |
|------------|------------------------------------|-----|------|
| Gender     | Male                               | 106 | 72.1 |
|            | Female                             | 41  | 27.9 |
| Age        | 20–30                              | 53  | 36.1 |
|            | 31–40                              | 77  | 52.4 |
|            | 41–50                              | 16  | 10.9 |
|            | Above 50                           | 1   | 0.7  |
| Education  | Diploma                            | 2   | 1.4  |
|            | Bachelor's degree                  | 94  | 63.9 |
|            | Master's degree                    | 51  | 34.7 |
| Sector     | Energy                             | 39  | 26.5 |
|            | Manufacturing                      | 39  | 26.5 |
|            | Construction                       | 39  | 26.5 |
|            | Infrastructure                     | 30  | 20.4 |
| Experience | Less than 5 years                  | 47  | 32.0 |
|            | 5–10 years                         | 74  | 50.3 |
|            | 11–15 years                        | 19  | 12.9 |
|            | More than 15 years                 | 7   | 4.8  |
| Position   | Engineer                           | 68  | 46.3 |
|            | Sustainability specialist          | 34  | 23.1 |
|            | Project manager                    | 32  | 21.8 |
|            | Operations manager                 | 7   | 4.8  |
|            | Other technical role or not stated | 6   | 4.1  |

### 3.5 Analysis Strategy

The analysis followed the two-step approach [38]. First, exploratory factor analysis (EFA; maximum likelihood with oblimin rotation) and parallel analysis with 500 random data sets examined the dimensional structure of the 20 items. Second, confirmatory factor analysis (CFA) assessed convergent validity through loadings, composite reliability (CR), and average variance extracted (AVE), and discriminant validity through the heterotrait-monotrait ratio (HTMT < 0.85) [39] and the Fornell–Larcker criterion [40]. Third, the structural model was estimated by maximum likelihood, and indirect effects were tested with 2,000 percentile bootstrap resamples. Model fit was judged against CFI and  $TLI \geq 0.90$ ,  $RMSEA \leq 0.08$ , and  $SRMR \leq 0.08$  [41]. Common method variance was assessed with Harman's single-factor test, a single-factor CFA, and full-collinearity variance inflation factors (VIFs) [42]. Analyses were run in Python using the `semopy` and `factor_analyzer` packages.

With 147 cases and 15 retained indicators (9.8 cases per indicator), the sample meets common minimums for a model of four latent constructs with three to five indicators each [43].

## 3.6 Transparency Statement

The instrument was designed to measure five constructs. Because preliminary analysis showed that CE and I5 items could not be empirically separated, the measurement structure was re-examined through EFA, and the model was re-specified before confirmatory testing. Both steps used the same sample. The findings should therefore be read as a theory-informed model that requires confirmation on an independent sample.

## 4. Results

### 4.1 Dimensional Structure

The data were suitable for factoring ( $KMO = 0.833$ ; Bartlett's  $\chi^2 = 1196.4$ ,  $p < 0.001$ ). Parallel analysis retained three factors: the observed eigenvalues of 6.17, 2.30, and 1.90 exceeded the 95th-percentile random values of 1.87, 1.68, and 1.55, whereas the fourth eigenvalue (1.21) fell below its random counterpart (1.45). All eight CE and I5 items loaded on a single factor. EE1–EE3 loaded with CEF1–CEF3 in the three-factor solution and separated from them in the five-factor solution. EE4 (0.64) and CEF4 (0.82) loaded on the SP factor rather than on their intended constructs.

### 4.2 Merging CE and I5

In a CFA of the original 20-item instrument, the latent correlation between CE and I5 was 0.96 (HTMT = 0.943), and constraining them to a single factor did not worsen fit ( $\Delta\chi^2 = 4.28$ ,  $\Delta df = 4$ ,  $p = 0.37$ ). The two were therefore modeled as one construct, DCC. The original five-factor model also fitted poorly (CFI = 0.771,  $RMSEA = 0.103$ ), with AVE below 0.50 for four of the five constructs.

### 4.3 Measurement Model

Five items were removed: EE4 and CEF4 (cross-loading on SP), CE1 (loading 0.37), I53 (loading 0.45), and CE3 (large residual correlations with EE and CEF items, up to 0.22). The final 15-item model fitted

acceptably:  $\chi^2(84) = 138.03$ , CFI = 0.926, TLI = 0.908, RMSEA = 0.066, SRMR = 0.070. Table II reports the loadings and reliability statistics.

TABLE II. MEASUREMENT MODEL (N = 147)

| Construct                                                                                                                                                                                                                                     | Item (standardized loading)                                | $\alpha$ | CR    | AVE   |
|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------|----------|-------|-------|
| DCC                                                                                                                                                                                                                                           | CE2 (0.66), CE4 (0.56), I51 (0.55), I52 (0.58), I54 (0.58) | 0.716    | 0.723 | 0.345 |
| EE                                                                                                                                                                                                                                            | EE1 (0.62), EE2 (0.70), EE3 (0.79)                         | 0.741    | 0.744 | 0.494 |
| CEF                                                                                                                                                                                                                                           | CEF1 (0.68), CEF2 (0.74), CEF3 (0.78)                      | 0.779    | 0.778 | 0.540 |
| SP                                                                                                                                                                                                                                            | SP1 (0.54), SP2 (0.78), SP3 (0.79), SP4 (0.82)             | 0.823    | 0.825 | 0.546 |
| Note: Model fit: $\chi^2(84) = 138.03$ , CFI = 0.926, TLI = 0.908, RMSEA = 0.066, SRMR = 0.070. All loadings $p < 0.001$ . DCC = digital-circular capability; EE = energy efficiency; CEF = cost efficiency; SP = sustainability performance. |                                                            |          |       |       |

All loadings were significant ( $p < 0.001$ ), and CR exceeded 0.70 for every construct. AVE for DCC (0.345) and EE (0.494) fell below 0.50. Following Fornell and Larcker [40], convergent validity can still be considered adequate when CR exceeds 0.60, but this is reported as a limitation.

## 4.4 Discriminant Validity and Common Method Variance

Table III reports the discriminant validity statistics. All HTMT values were below 0.85. The Fornell–Larcker criterion held for every pair except EE–CEF ( $\sqrt{\text{AVE}}$  of EE = 0.703 <  $r = 0.745$ ). Because HTMT is the more sensitive criterion [39] and was satisfied (0.746), EE and CEF were retained as distinct constructs.

TABLE III. DISCRIMINANT VALIDITY

| DCC                                                                                                                                                                                              | DCC          | EE           | CEF          | SP           |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------|--------------|--------------|--------------|
|                                                                                                                                                                                                  | <b>0.587</b> | <b>0.344</b> | <b>0.301</b> | <b>0.538</b> |
| EE                                                                                                                                                                                               | 0.346        | 0.703        | 0.746        | 0.522        |
| CEF                                                                                                                                                                                              | 0.244        | 0.745        | 0.735        | 0.609        |
| SP                                                                                                                                                                                               | 0.563        | 0.537        | 0.609        | 0.739        |
| Mean (SD)                                                                                                                                                                                        | 4.29 (0.56)  | 4.00 (0.76)  | 3.89 (0.83)  | 4.24 (0.72)  |
| Note: Diagonal (bold) = $\sqrt{\text{AVE}}$ ; below the diagonal = latent correlations; above the diagonal = HTMT ratios. Means and standard deviations are for construct scores on a 1–5 scale. |              |              |              |              |

Common method variance was unlikely to bias the results. The first unrotated factor explained 30.8% of the variance across the 20 items (33.2% across the 15 retained items). A single-factor CFA fitted far

worse than the four-factor model (CFI = 0.661, RMSEA = 0.137). Full-collinearity VIFs ranged from 1.24 to 1.68, below the 3.3 threshold [42].

## 4.5 Structural Model and Hypothesis Testing

The full structural model estimated all six paths among DCC, EE, CEF, and SP (Table IV). Two paths were not significant: DCC → CEF ( $\beta = -0.015$ ,  $p = 0.879$ ) and EE → SP ( $\beta = 0.026$ ,  $p = 0.875$ ). Removing them did not worsen fit ( $\Delta\chi^2 = 0.06$ ,  $\Delta df = 2$ ,  $p = 0.97$ ), so the more parsimonious model was retained:  $\chi^2(86) = 138.09$ , CFI = 0.929, TLI = 0.913, RMSEA = 0.064. The retained model explains 11.9% of the variance in EE, 55.8% in CEF, and 55.9% in SP.

TABLE IV. FULL AND RETAINED STRUCTURAL MODELS

| Path                                                                                                                                      | Full model $\beta$    | p       | Retained model $\beta$ | p       |
|-------------------------------------------------------------------------------------------------------------------------------------------|-----------------------|---------|------------------------|---------|
| DCC $\rightarrow$ EE                                                                                                                      | 0.347                 | 0.004   | 0.345                  | 0.003   |
| DCC $\rightarrow$ CEF                                                                                                                     | -0.015                | 0.879   | —                      | —       |
| EE $\rightarrow$ CEF                                                                                                                      | 0.751                 | < 0.001 | 0.747                  | < 0.001 |
| DCC $\rightarrow$ SP                                                                                                                      | 0.437                 | < 0.001 | 0.439                  | < 0.001 |
| EE $\rightarrow$ SP                                                                                                                       | 0.026                 | 0.875   | —                      | —       |
| CEF $\rightarrow$ SP                                                                                                                      | 0.484                 | 0.006   | 0.503                  | < 0.001 |
| $\chi^2$ (df)                                                                                                                             | 138.03 (84)           |         | 138.09 (86)            |         |
| CFI / TLI                                                                                                                                 | 0.926 / 0.908         |         | 0.929 / 0.913          |         |
| RMSEA                                                                                                                                     | 0.066                 |         | 0.064                  |         |
| R <sup>2</sup> (EE / CEF / SP)                                                                                                            | 0.120 / 0.557 / 0.556 |         | 0.119 / 0.558 / 0.559  |         |
| Note: Standardized coefficients, maximum likelihood estimation, N = 147. $\Delta\chi^2$ between models = 0.06, $\Delta df$ = 2, p = 0.97. |                       |         |                        |         |

Table V reports the hypothesis tests, and Fig. 1 shows the retained model. H1–H4 were supported. The serial indirect effect DCC → EE → CEF → SP was significant ( $\beta = 0.130$ ;  $B = 0.119$ , 95% CI [0.021, 0.259]), supporting H5, and accounts for 23% of the total effect of DCC on SP (0.130/0.568), indicating partial mediation. H6 was not supported. In the full six-path model, the same indirect effect was positive, but its interval included zero ( $B = 0.116$ , 95% CI [- 0.041, 0.317]); the high EE–CEF correlation widens the intervals when both paths to SP compete.

TABLE V. HYPOTHESIS TESTS (N = 147, 2,000 BOOTSTRAP RESAMPLES)

| Hypothesis                                                                                                                                                                                                                     | Path                    | $\beta$ | B      | p or 95% CI of B | Result        |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------|---------|--------|------------------|---------------|
| H1                                                                                                                                                                                                                             | DCC → EE                | 0.345   | 0.420  | p = 0.003        | Supported     |
| H2                                                                                                                                                                                                                             | EE → CEF                | 0.747   | 0.923  | p < 0.001        | Supported     |
| H3                                                                                                                                                                                                                             | CEF → SP                | 0.503   | 0.308  | p < 0.001        | Supported     |
| H4                                                                                                                                                                                                                             | DCC → SP (direct)       | 0.439   | 0.404  | [0.129, 0.876]   | Supported     |
| H5                                                                                                                                                                                                                             | DCC → EE → CEF → SP     | 0.130   | 0.119  | [0.021, 0.259]   | Supported     |
| H6                                                                                                                                                                                                                             | DCC → CEF (alternative) | -0.015  | -0.023 | p = 0.879        | Not supported |
| Total effect                                                                                                                                                                                                                   | DCC → SP                | 0.568   | 0.524  | [0.193, 1.065]   | —             |
| Note: $\beta$ = standardized coefficient; B = unstandardized coefficient. H1–H5 and the total effect are from the retained model; H6 is from the full six-path model. Confidence intervals are percentile bootstrap intervals. |                         |         |        |                  |               |

## 4.6 Robustness Checks

The serial indirect effect and the direct effect remained significant in every alternative sample and specification (Table VI). The last check removes SP2 and SP4, which mention intelligent technologies and could make the DCC → SP link circular. The direct effect fell from 0.439 to 0.331 but remained significant, so the result does not depend on item wording.

TABLE VI. ROBUSTNESS OF THE RETAINED MODEL

| Specification                                                                                                                                                                        | N   | CFI   | RMSEA | Indirect $\beta$ | Indirect B 95% CI | Direct $\beta$ | SP R <sup>2</sup> |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----|-------|-------|------------------|-------------------|----------------|-------------------|
| Main analysis                                                                                                                                                                        | 147 | 0.929 | 0.064 | 0.130            | [0.021, 0.259]    | 0.439          | 0.559             |
| All responses (no screening)                                                                                                                                                         | 159 | 0.945 | 0.064 | 0.190            | [0.052, 0.323]    | 0.462          | 0.625             |
| Core engineering roles only                                                                                                                                                          | 141 | 0.915 | 0.070 | 0.132            | [0.018, 0.315]    | 0.502          | 0.606             |
| SP without technology-worded items (SP1, SP3)                                                                                                                                        | 147 | 0.951 | 0.053 | 0.167            | [0.023, 0.285]    | 0.331          | 0.636             |
| Note: Indirect = serial indirect effect DCC → EE → CEF → SP; 2,000 bootstrap resamples in each specification. All direct effects were significant (bootstrap 95% CIs excluded zero). |     |       |       |                  |                   |                |                   |

Control variables did not change the pattern. In a regression of SP on construct scores with experience, education, gender, and sector as controls (HC3 robust standard errors), DCC ( $\beta = 0.295$ ,  $p = 0.014$ ) and CEF ( $\beta = 0.364$ ,  $p = 0.008$ ) remained significant, EE did not ( $\beta = 0.124$ ,  $p = 0.267$ ), and no control variable was significant. The controls alone explained 10.8% of the variance in SP, and SP did not differ by sector (Kruskal–Wallis  $H = 3.90$ ,  $p = 0.27$ ).

## 5. Discussion

### 5.1 Digital-Circular Capability as One Construct

The first finding is that respondents did not distinguish circular practices from intelligent technologies. One interpretation is that, in practice, the two are adopted together: AI and IoT systems are often the means through which material recovery and resource monitoring are carried out, so organizations experience them as a single capability bundle. This interpretation is consistent with the convergence described in the literature [23], [4], [5]. An alternative explanation is that the items, all phrased at the level of the organization, captured a general tendency toward modernization rather than two distinct practices. The present data cannot separate these explanations, which is why DCC should be validated with more specific items and independent samples.

### 5.2 The Serial Pathway

The results suggest that DCC supports sustainability partly through an energy-to-cost chain. DCC is associated with higher energy efficiency ( $\beta = 0.345$ ), energy efficiency with higher cost efficiency ( $\beta = 0.747$ ), and cost efficiency with better sustainability performance ( $\beta = 0.503$ ). This pattern is consistent with NRBV, in which resource efficiency links environmental and economic gains [12], [13], and with evidence that energy efficiency measures bring wider cost benefits [29], [30]. The direct effect of DCC on SP ( $\beta = 0.439$ ) remained substantial, so the chain explains part, not all, of how DCC relates to sustainability.

The lack of a direct DCC  $\rightarrow$  CEF effect is notable. Studies of predictive maintenance and automation often expect direct cost savings, yet in this sample the cost benefits associated with DCC appeared to arrive through energy efficiency. Because the design is cross-sectional, this pattern indicates association and mediation consistent with the theory, not proof of causal sequence.

### 5.3 Energy Efficiency and Sustainability Performance

EE did not have a direct effect on SP once CEF was in the model ( $\beta = 0.026$ ,  $p = 0.875$ ). One reading is that the sustainability value of energy savings is realized when they are translated into economic gains. A statistical reading is equally plausible: EE and CEF are strongly correlated ( $r = 0.75$ ), so the model may not be able to separate their unique contributions. Both readings should be tested with more distinct measures.

### 5.4 Theoretical Contributions

The study makes three contributions. First, it proposes DCC as an integrated construct, extending prior work that treats CE and digital technology as separate variables [22], [4]. Second, it specifies and tests a serial mechanism,  $DCC \rightarrow EE \rightarrow CEF \rightarrow SP$ , responding to calls to explain how environmental capabilities are turned into performance [13]. Third, it adds evidence from engineering organizations in Saudi Arabia, complementing studies of manufacturing firms in the same country [6], [7].

## 5.5 Practical Implications

For engineering and project managers, the findings point to four actions:

- Plan circular practices and intelligent technologies as one program rather than as separate initiatives, for example by using IoT monitoring and AI analytics to manage material recovery and energy use together.
- Make energy monitoring and energy management a core deliverable of digital and circular projects, since energy efficiency is the first link in the pathway.
- Track the cost effects of energy efficiency explicitly, so that energy savings are translated into measurable economic results that sustain management support.
- Do not expect all sustainability benefits to flow through cost; the direct effect of DCC suggests that some benefits arise independently of the energy-to-cost pathway.

For policymakers, the results support aligning digital transformation initiatives under Saudi Vision 2030 with circular economy and energy efficiency programs, so that investment in technology is directed toward measurable resource savings.

## 5.6 Limitations and Future Research

The study has several limitations.

- Same-sample derivation: EFA, item purification, and CFA used a single sample of 147. A second sample of comparable size is needed to confirm the 15-item model and move the findings from exploratory to confirmatory.
- Post hoc path removal: two non-significant paths were dropped after estimation, justified by a non-significant  $\Delta\chi^2$ ; the full six-path results are reported in Table IV.
- Convergent validity: AVE for DCC (0.345) and EE (0.494) is below 0.50. DCC is broad by design, which lowers shared variance, and future research should refine its items.
- EE–CEF closeness: the Fornell–Larcker criterion is not met for this pair, although HTMT is (0.746).
- Item wording: CEF items attribute savings to circular practices, intelligent technologies, and predictive maintenance, so CEF measures the perceived cost benefits of operational improvement rather than accounting cost efficiency. Future studies should use objective or more general cost measures.
- Scope of I5: the technology items reflect digital technologies shared with Industry 4.0; the human-centric and resilience dimensions of I5 were not measured.

- Design: the study is cross-sectional and self-reported, uses non-probability sampling, and relies on single key informants, so causal direction is inferred from theory rather than tested. Longitudinal and multi-source designs would strengthen causal inference.

## 6. Conclusion

This study proposed and tested a serial mediation model of how digital-circular capability relates to sustainability performance in engineering organizations. Using a screened sample of 147 professionals in Saudi Arabia, it found that circular practices and intelligent technologies form a single capability, that this capability is associated with higher energy efficiency, which is associated with higher cost efficiency, which in turn is associated with better sustainability performance, and that a substantial direct effect remains alongside this chain. The model explains 55.9% of the variance in sustainability performance and holds across alternative samples and specifications. By reporting openly that the model was re-specified from the data, the study offers a testable foundation for confirmatory research in sustainable engineering management.

## Declarations

## Author Contribution

M.A.F. conceived and designed the study, developed the questionnaire, collected and analysed the data, prepared all figures and tables, and wrote and reviewed the manuscript.

## Acknowledgement

Generative AI (Claude, Anthropic) was used to assist with language editing, literature screening and writing the statistical analysis code.

## Data Availability

The anonymized survey dataset generated and analyzed during the current study is available from the corresponding author on reasonable request.

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## Figures

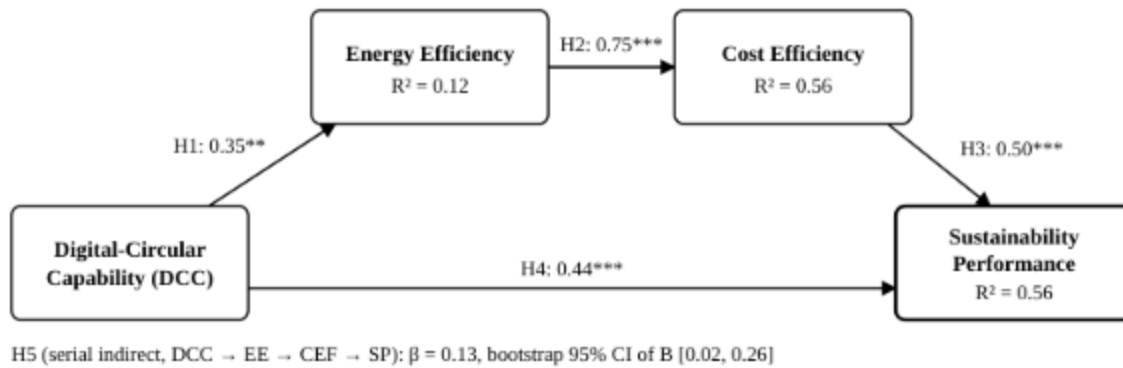


**Figure 1**

Retained structural model (standardized coefficients, N = 147). \*\*  $p < 0.01$ ; \*\*\*  $p < 0.001$ . Non-significant paths (DCC → CEF, EE → SP) removed.

## Supplementary Files

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