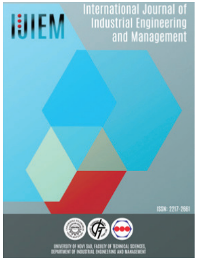
ISSN 2683-345X
journal homepage: http://ijiemjournal.uns.ac.rs/



International Journal of Industrial Engineering and Management

2026 / ARTICLE-IN-PRESS / 418

Original research article

Investigating the Impact of Circular Economy Strategies on Financial Performance with the Mediating Role of Human-Centric Sustainable Supply Chain Management

B. Al Oraini[a,*] 0009-0009-3549-8172, S. Ibrahim Mohammad[b,c] 0000-0001-6156-9063,
A. Vasudevan[c,d] 0000-0002-9866-4045, L. Salinas[e,f] 0000-0002-3264-6805,
S. Otamurodov[g] 0000-0003-2464-8103, B. Berdiyarov[h] 0000-0001-8591-6840,
K. Ulugbek[i] 0000-0002-3589-373X

[a] *Department of Business Administration, College of Business and Economics, Qassim University, Qassim, Saudi Arabia;*
[b] *School of Business, Al al-Bayt University, Mafraq, Jordan;*
[c] *INTI International University, Negeri Sembilan, Malaysia;*
[d] *Shinawatra University, 99 Moo 10, Bangtoey, Samkhok, Pathum Thani 12160 Thailand;*
[e] *Department of Computers Techniques Engineering, College of Technical Engineering, Najaf, Iraq;*
[f] *Department of Industrial Engineering, New Jersey Institute of Technology, Newark, New Jersey, USA;*
[g] *Department of Economics, Termez University of Economics and Service, Termez, Uzbekistan;*
[h] *Department of Microeconomics, National University of Uzbekistan named after Mirzo Ulugbek, Tashkent, Uzbekistan;*
[i] *Namangan State Technical University, Namangan, Uzbekistan*

ABSTRACT

Industry 5.0 has shifted attention from automation alone to the human conditions under which Circular Economy Strategies (CES) create financial value. This study examines whether Human-Centric Sustainable Supply Chain Management (HC-SSCM) mediates the relationship between CES and Financial Performance (FP) in Saudi manufacturing firms. Data were gathered through a structured questionnaire from 240 firms and analyzed with a two-stage design that combined Partial Least Squares Structural Equation Modeling and Artificial Neural Network (ANN) analysis. The results show that CES has a positive direct association with competitor-relative FP and a strong positive association with HC-SSCM, while HC-SSCM is also positively associated with Financial Performance. The indirect association from CES to FP through HC-SSCM is significant, with a Variance Accounted For of 47.9%, indicating complementary partial mediation. ANN results further show that cognitive ergonomic support and human-robot collaboration are stronger predictors of self-reported FP than the technical circular variables alone. These findings suggest that circular strategies are more strongly associated with favorable financial outcomes when reverse-logistics and recovery activities are supported by worker-centered decision support, collaborative technologies, and adaptive problem solving.

ARTICLE INFO

Article history:

Received December 8, 2025
Revised April 17, 2026
Accepted May 5, 2026
Published online June 26, 2026

Keywords:
Circular economy;
Financial performance;
Human-centricity;
Industry 5.0;
Sustainable supply chain management

*Corresponding author:
Badrea Al Oraini
barieny@qu.edu.sa

Published by the University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia.

https://doi.org/10.24867/IJIEM-418

1. Introduction

The global manufacturing landscape is currently undergoing a profound paradigm shift, transitioning from the technology-driven efficiencies of Industry 4.0 (I4.0) toward the value-oriented principles of Industry 5.0 (I5.0) [1]. While the former era prioritized automation, digitization, and machine-to-machine communication to optimize output, the emerging I5.0 paradigm fundamentally reintroduces the human operator into the production ecosystem, emphasizing resilience, sustainability, and human-centricity [2]. This transition is not merely a theoretical evolution but a critical industrial imperative driven by the urgent need to align economic growth with the United Nations Sustainable Development Goals [3]. As organizations face mounting pressure to adopt Circular Economy Strategies (CES), moving away from linear "take-make-dispose" models, the complexity of supply chains has increased exponentially. Consequently, the ability to capitalize on these circular strategies financially now depends less on pure technological speed and more on the adaptability and cognitive problem-solving capabilities of the human workforce [4], [5]. This study posits that the intersection of human-centricity and circularity represents an unexplored frontier for achieving superior Financial Performance (FP) in Sustainable Supply Chain Management (SSCM).

The current body of literature regarding SSCM is dominated by technocentric perspectives. Extensive research has demonstrated how digital enablers such as the Internet of Things (IoT) and big data analytics drive resource efficiency [6]. Within this domain, the Circular Economy (CE) has emerged as a dominant framework for minimizing waste through closed-loop systems, remanufacturing, and Reverse Logistics (RL) [7]-[9]. However, the relationship between CE adoption and corporate FP remains a subject of intense debate. While proponents argue that circular practices reduce material costs and open new revenue streams [10], a significant counter-stream of literature suggests that the operational complexity and high initial investment costs of CE often erode short-term profitability [11]. Furthermore, existing frameworks often treat the human element as a secondary factor or a source of error to be minimized by automation. In contrast, the nascent literature on I5.0 argues for the *Operator 5.0* concept, where technology serves as a collaborative tool to enhance, rather than replace, human capabilities [12]-[14]. Despite this theoretical advancement, empirical studies linking I5.0 human-centric practices—such as cognitive ergonomic support and human-robot collaboration—directly to the financial success of circular initiatives are scarce. Most studies remain siloed: they either analyze CE-FP links without considering human factors or discuss human-centricity without robust financial quantification. To clarify the divergent trajectories in the literature, Table 1 presents a typological comparison between the established I4.0 approaches and the emerging I5.0 perspectives within supply chain research. This comparison highlights the fundamental shift from techno-efficiency to human-resilience required for the next generation of industrial value creation.

This shift from techno-efficiency to human-resilience becomes analytically meaningful only when the human element is specified at the level of supply-chain work design. HC-SSCM is defined here as the operational capability through which reverse-logistics and recovery work systems place worker well-being, judgment, learning, safety, and collaborative decision support at the center of circular execution. In practice, this capability appears through cognitive ergonomic support, human-robot collaboration, and adaptive problem solving in recovery flows [12]-[14], [18], [19]. HC-SSCM differs from human capital because it does not denote the stock of employee

Table 1. Typological comparison of I4.0 and I5.0 paradigms in supply chain literature [15]-[17].

Feature	I4.0 (Technocentric Paradigm)	I5.0 (Human-Centric Paradigm)
Primary Driver	Automation, IoT, and digitization for maximum efficiency.	Human-centricity, resilience, and sustainability.
Role of Human	Operator as a supervisor or bottleneck; focus on labor reduction.	"Operator 5.0"; human-robot collaboration and cognitive empowerment.
Circular Economy	Focus on automated sorting and material tracking.	Focus on complex decision-making in RL and repair.
Value Proposition	Cost reduction through speed and precision.	Value creation through adaptability and personalization.
Key Limitation	Fragility during disruptions; rigid systems.	High complexity in managing human-tech interfaces.

knowledge and skills in isolation. It also differs from organizational learning because it does not refer to the firm's general capacity to create, store, or transfer knowledge across activities. The construct captures the way those human assets are embedded in recovery routines, interface design, escalation protocols, and cross-functional coordination during daily circular operations [20]-[22]. A firm may therefore possess skilled employees and active learning mechanisms yet still fail to convert CE strategies into financial gains if reverse-logistics work systems do not support safe judgment and rapid adaptation. Industrial transition settings are therefore especially suitable for examining how human-centric work design converts circular complexity into financial resilience.

This research focuses on the manufacturing sector within Saudi Arabia, a region currently undergoing a massive industrial transformation under Vision 2030. This context provides a unique "living lab" to observe the leapfrogging from traditional manufacturing to I5.0 standards. To rigorously investigate the identified relationships, this study employs a dual-stage analytical approach combining Partial Least Squares Structural Equation Modeling (PLS-SEM) and Artificial Neural Network (ANN) analysis. The justification for this hybrid methodology is two-fold. First, PLS-SEM is well-suited for exploratory theory building in complex models with non-normal data distributions [23]-[25]. Second, the integration of ANN is essential to capture the non-linear and compensatory relationships between human factors and financial outcomes, which linear models frequently miss. This methodological innovation allows for a more precise predictive understanding of how cognitive support systems influence the bottom line. That operational role also clarifies why HC-SSCM can be examined through the Resource-Based View (RBV). Within circular supply chains, this capability is valuable because it reduces sorting and recovery errors, shortens exception-resolution time, and improves the conversion of returned materials into saleable output. It is relatively rare when decision-support routines, collaborative technologies, and worker-centered recovery design are integrated across the full reverse-logistics process rather than implemented as isolated practices. It is difficult to imitate because it is embedded in firm-specific workflow design, accumulated operator experience, and interaction routines between people and technologies. It is not readily substitutable because reverse flows continue to involve ambiguous quality states, safety trade-offs, and context-specific repair decisions that pure automation cannot absorb consistently [12]-[14], [18], [20]-[22]. Human capital and organizational learning remain important antecedent resources under this logic, but HC-SSCM is the operational capability that mobilizes those inputs inside circular execution. This framing motivates the conceptual model developed and tested in the present analysis.

The primary aim of this manuscript is to develop and validate a conceptual model that positions human-centric SSCM practices as the essential catalyst for unlocking the financial value of CE strategies. To address the identified gaps, this study investigates the following inquiries: How do I5.0 human-centric paradigms influence the relationship between CE adoption and corporate financial performance? specifically, does the integration of cognitive support in RL act as a predictor for higher cost recovery and profitability? The specific objectives of this study are: (i) To empirically measure the impact of human-centric SSCM practices on the FP of manufacturing firms transitioning to I5.0, (ii) To analyze the mediating role of workforce resilience and cognitive support in the relationship between circular strategies and financial outcomes, (iii) To evaluate the predictive validity of the proposed model using a hybrid PLS-SEM and ANN approach, thereby identifying non-linear determinants of profitability.

2. Methodology

2.1 Research Design and Study Location

To rigorously address the research objectives regarding the intersection of I5.0 paradigms, CES, and FP, this study employed a quantitative, cross-sectional research design. This approach was selected to capture a snapshot of the current industrial transition within the Kingdom of Saudi Arabia, a region currently undergoing rapid economic diversification under the Vision 2030 framework. The specific study locations were strategically selected to represent the industrial core of the nation, focusing on the primary industrial cities managed by the Saudi Authority for Industrial Cities and Technology Zones (MODON). These included Jubail Industrial City, Yanbu, Riyadh (specifically the Second Industrial City), and Dammam. These regions were chosen due to their high concentration of manufacturing firms transitioning from heavy petrochemical dependence toward advanced manufacturing and SSCM practices.

The epistemological stance of this research follows a positivist paradigm and separates explanation from prediction. Phase one employed PLS-SEM to validate the reflective measurement model, test the theorized direct and indirect associations, and estimate latent variable scores under distributional conditions that fit exploratory, prediction-oriented models [23]-[25]. Phase two then used ANN analysis only after the measurement and structural relations had been established. This sequence was selected because the study required both latent-variable theory testing and a flexible prediction stage capable of capturing non-compensatory and non-linear patterns among the validated feature domains. Generalized structured component analysis and Bayesian SEM remain important alternatives for modeling complex relationships, but the present objective was not to replace latent-variable estimation with a single integrated estimator. The objective was to preserve measurement validity and mediation testing in the first stage, then assess whether the retained circular and human-centric domains showed additional non-linear predictive strength in the second stage [23]-[25]. The cross-sectional design supports theory-consistent association testing rather than strict causal identification, so the directional ordering of CES, HC-SSCM, and FP is justified by the implementation logic of circular operations, in which strategic design choices precede work-system adaptation and financial outcomes. Overfitting risk in the ANN stage was managed through ten-fold cross-validation and comparison of training and testing Root Mean Square Error across folds.

2.2 Sampling Strategy and Participant Recruitment

The target population comprised operational managers, supply chain directors, and industrial engineers working within medium-to-large-scale manufacturing enterprises in the identified Saudi regions. To ensure the representativeness of the sample and minimize selection bias, a stratified random sampling technique was utilized. The strata were defined based on industrial sectors critical to the circular economy, including electronics, automotive assembly, construction materials, and packaging.

The determination of the minimum required sample size was conducted using an a priori power analysis to ensure sufficient statistical power to detect medium effect sizes. However, to account for the asymptotic consistency required by PLS-SEM and the training data requirements for ANN, a more rigorous calculation was applied. The sample size was derived based on the complexity of the structural model, specifically targeting a power level of 0.80 and a significance level of 0.05.

Equation (1) outlines the calculation for the minimum sample size adjusted for a finite population, ensuring the gathered data possesses statistical representativeness relative to the estimated total number of manufacturing units in the target sectors [26].

$$n = \frac{N \times Z^2 \times p \times (1-p)}{E^2 \times (N-1) + Z^2 \times p \times (1-p)} \tag{1}$$

where n represents the required sample size, N denotes the population size estimated from chamber of commerce registries, Z is the critical value for the confidence level (1.96 for 95%), p represents the estimated proportion of the population adopting I5.0 standards (conservatively set at 0.5 to maximize sample size), and E is the margin of error (set at 0.05).

Based on this calculation and anticipating a response rate typical of industrial surveys, 600 invitations were distributed. A total of 240 valid, complete responses were retained for analysis after a rigorous data screening process, yielding a final sample size (N=240) that exceeds the "10-times rule" often cited for PLS-SEM robustness, effectively satisfying the requirement for stable model convergence.

2.3 Instrument Development and Data Acquisition Protocols

Data were gathered through a structured self-administered questionnaire administered to qualified respondents in the sampled firms. The instrument was developed in four stages. First, measurement items were adapted from validated studies on CES, I5.0 human-centric operations, and competitor-relative FP [7], [8], [10], [12]-[14], [27], [28]. Second, contextual wording was refined to fit reverse logistics, resource recovery, and Saudi manufacturing practice. Third, 15 academic experts and industry practitioners reviewed the instrument for relevance, clarity, and domain fit. Fourth, a pilot test was conducted to remove redundant items and improve content validity before the main survey. The final questionnaire contained four sections covering respondent demographics, CES, HC-SSCM, and competitor-relative FP, and all latent variables were measured on a 7-point Likert scale ranging from 1 = Strongly Disagree to 7 = Strongly Agree. FP therefore reflects managerial assessments of profitability, cost recovery, and relative market outcomes rather than audited accounting records. After collection, responses were screened for completeness, outliers, and inconsistent response patterns, and 240 valid questionnaires were retained for analysis. SmartPLS 4 was used for measurement-model assessment, structural-model estimation, bootstrapping, and latent-score extraction, whereas SPSS was used for ANN analysis and ten-fold cross-validation. Common method bias was mitigated ex ante through anonymity protection, proximal separation of construct sections, and item randomization. Ex post assessment treated method bias separately from construct validity through Harman's single-factor screening, full-collinearity diagnostics, and the Heterotrait-Monotrait ratio reported in the measurement model, while ANN inputs were standardized and screened for multicollinearity before network estimation.

2.4 Mathematical Modeling of Latent Variables

The theoretical model posits that the observed variables (survey items) are reflective manifestations of the underlying latent constructs. In the PLS-SEM framework, the relationship between the latent variable and its indicators is defined by the outer measurement model. Equation (2) formalizes this reflective measurement model, relating the manifest variables to their corresponding latent constructs alongside the measurement error [29], [30].

$$x_{jk} = \lambda_{jk}\xi_j + \delta_{jk} \tag{2}$$

where x_{jk} represents the *k*-th indicator of the *j*-th latent variable ξ_j. The term λ_{jk} denotes the outer loading, which quantifies the strength of the relationship between the indicator and the construct, while δ_{jk} represents the random measurement error. This equation is fundamental to the analysis as it facilitates the evaluation of how well the theoretical concepts—such as human-centricity—are captured by the empirical data.

Following the establishment of the measurement model, the structural relationships between the latent variables were modeled. Equation (3) describes the inner structural model, which defines the causal paths between the exogenous variables (CES) and endogenous variables (HC-SSCM and FP) [31].

$$\eta_i = \sum_j \beta_{ji}\xi_j + \sum_k \gamma_{ki}\eta_k + \zeta_i \tag{3}$$

where η_i represents the endogenous latent variable (e.g., Financial Performance), ξ_j denotes the exogenous latent variables, and β_{ji} and γ_{ki} are the path coefficients representing the strength and direction of the relationships. The term ζ_i represents the residual variance (disturbance term) not explained by the predictor variables. This linear equation allows the testing of the primary research hypotheses regarding the direct and mediated effects of circular strategies on profitability.

2.4.1 Analytical Techniques: Phase I (PLS-SEM)

The primary data analysis was conducted using SmartPLS 4 software. PLS-SEM was selected over covariance-based SEM (CB-SEM) due to its superior ability to handle non-normal data distributions and its focus on maximizing the explained variance (R^2) of the endogenous constructs, which aligns with the predictive objective of this study.

2.4.2 Measurement Model Assessment

The reliability and validity of the reflective measurement model were evaluated through several specific metrics. Internal consistency reliability was assessed using Composite Reliability (CR). Unlike Cronbach's alpha, which assumes equal factor loadings, CR provides a more accurate estimate of reliability for PLS-SEM. Equation (4) presents the formula for Composite Reliability [32], [33], [34].

$$\text{CR} = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum \text{Var}(\delta_i)} \tag{4}$$

where λ_i is the standardized outer loading of the indicator *i*, and $\text{Var}(\delta_i)$ is the variance of the measurement error, calculated as $1-\lambda_i^2$. A CR value of 0.70 or higher is required to establish internal consistency.

Convergent validity was assessed using the Average Variance Extracted (AVE). This metric determines the amount of variance a construct captures from its indicators relative to the amount due to measurement error. Equation (5) defines the AVE calculation [27], [28], [35].

$$\text{AVE} = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum \text{Var}(\delta_i)} \tag{5}$$

An AVE value greater than 0.50 indicates that the construct explains more than half of the variance of its indicators, confirming convergent validity.

Discriminant validity was rigorously tested using the Heterotrait-Monotrait ratio of correlations (HTMT), which has been shown to be more sensitive than the traditional Fornell-Larcker criterion. Equation (6) illustrates the HTMT computation [36], [37].

$$\mathrm{HTMT}_{ij} = \frac{\dfrac{1}{K_i K_j}\sum_{g=1}^{K_i}\sum_{h=1}^{K_j}|r_{ig,jh}|}{\sqrt{\left(\dfrac{2}{K_i(K_i-1)}\sum_{g=1}^{K_i-1}\sum_{h=g+1}^{K_i} r_{ig,ih}\right)\left(\dfrac{2}{K_j(K_j-1)}\sum_{g=1}^{K_j-1}\sum_{h=g+1}^{K_j} r_{jg,jh}\right)}} \tag{6}$$

In this context, K_i and K_j represent the number of indicators for constructs i and j, and r represents the correlations between indicators. Values below 0.85 (conservative threshold) or 0.90 confirm that the constructs are empirically distinct.

2.4.3 Structural Model Assessment

Upon validating the measurement model, the structural paths were evaluated. The explanatory power of the model was determined by the Coefficient of Determination (R^2). Equation (7) represents the calculation for R^2, which quantifies the proportion of variance in the endogenous variable explained by its predictors [38].

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \tag{7}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean. To assess the magnitude of the impact of omitting a specific predictor construct, the effect size (f^2) was calculated. Equation (8) details the f^2 computation [39].

$$f^2 = \frac{R^2_{\text{included}} - R^2_{\text{excluded}}}{1 - R^2_{\text{included}}} \tag{8}$$

Values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. Furthermore, the predictive relevance of the model was assessed using the Stone-Geisser criterion (Q^2) via a blindfolding procedure. Equation (9) calculates Q^2 [40].

$$Q^2 = 1 - \frac{\sum_D E_D}{\sum_D O_D} \tag{9}$$

where E_D represents the sum of squared prediction errors, and O_D is the sum of squared observations. A Q^2 value greater than zero confirms the model's predictive relevance for the endogenous construct.

2.4.4 Analytical Techniques: Phase II (Artificial Neural Network)

While PLS-SEM effectively tests linear relationships, human decision-making in supply chains is often non-linear and complex. Therefore, Phase II utilized an ANN to complement the PLS-SEM results. This study adopted a Multi-Layer Perceptron (MLP) architecture with a feed-forward back-propagation algorithm, utilizing SPSS software.

The significant predictors identified in the PLS-SEM analysis served as the neurons in the input layer, while FP served as the output neuron. A hidden layer was introduced to capture the non-linear interactions. To avoid overfitting, a ten-fold cross-validation procedure was employed, where 90% of the data was used for network training and 10% for testing.

Within that cross-validated design, the ANN inputs were derived from the validated PLS-SEM solution. SmartPLS 4 was used to export latent variable scores for CES, HC-SSCM, and FP. For the sensitivity analysis, the retained indicators were regrouped into four theory-based feature domains. Resource recovery loops captured the extent to which returned materials were sorted, recovered, and reintroduced into operations. Eco-design captured design choices that support disassembly, reuse, and material recovery. Cognitive ergonomic support captured the availability of decision-support interfaces, clear work instructions, rapid access to exception-handling information, and routines that reduce mental overload during inspection, sorting, and repair. Human-robot collaboration captured safe task sharing, coordinated handovers between operators and collaborative technologies, and the ability to reconfigure recovery tasks jointly when recovery conditions changed. Scores for each feature domain were computed as the mean of the standardized retained items within the same domain, normalized, and screened for multicollinearity before ANN estimation in SPSS. This procedure preserved construct validity in the explanatory model while enabling feature-level prediction in the neural network [12]-[14], [18], [20]-[25].

The signal processing within each neuron is governed by a transfer function. The input to a hidden node is a weighted sum of the inputs, modified by a bias term. Equation (10) defines the net input signal to a neuron [41].

$$\mathrm{Net}_j = \sum_{i=1}^{n} w_{ij} x_i + \theta_j \tag{10}$$

where w_{ij} is the synaptic weight connecting input neuron i to hidden neuron j, x_i is the input signal, and θ_j

is the bias. This net input is then processed through an activation function. The sigmoid function was selected for both the hidden and output layers due to its differentiability and suitability for continuous data. Equation (11) describes the sigmoid activation function used to generate the neuron's output [38].

$$f(\mathrm{Net}_j) = \frac{1}{1+e^{-\mathrm{Net}_j}} \tag{11}$$

This function maps the output to a range between 0 and 1, facilitating the normalization of data processing. To evaluate the accuracy of the ANN model, the Root Mean Square Error (RMSE) was calculated for both the training and testing datasets. Equation (12) presents the formula for RMSE, which serves as the primary objective function to be minimized during the network training process [42].

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i - T_i)^2} \tag{12}$$

where O_i is the observed value, T_i is the target (predicted) value, and N is the number of observations. Finally, a sensitivity analysis was performed to determine the "normalized importance" of each predictor. This step is crucial for Objective (iii), as it ranks the human-centric and circular variables based on their relative weight in predicting financial performance, thereby revealing which "operator 5.0" capabilities are most critical for cost recovery.

2.5 Methodological Synergy and Ethical Considerations

The integration of PLS-SEM and ANN ensures a comprehensive analysis. PLS-SEM provides the statistical significance and directionality of the paths (verifying the theoretical framework), while ANN assesses the magnitude and predictive accuracy of these paths (verifying practical applicability). This methodological synergy ensures that the results are not artifacts of linear assumptions but reflect the complex reality of modern industrial systems.

Ethical clearance was obtained from the institutional review board prior to data collection. Informed consent was a mandatory prerequisite for participation, and all data management protocols adhered to international standards for data privacy and confidentiality. The dataset was anonymized immediately upon acquisition to prevent the identification of specific firms or individuals.

3. Results and Discussions

3.1 Demographic Profile and Sample Characteristics

The empirical analysis is founded on a final dataset of 240 valid responses obtained from manufacturing entities operating within the Kingdom of Saudi Arabia (KSA). The data cleaning process involved the removal of incomplete surveys and outliers, ensuring that the subsequent PLS-SEM and ANN analyses were conducted on a robust dataset. The sample reflects a diverse cross-section of the industrial landscape, consistent with the stratified sampling strategy outlined in the methodology.

Table 2 presents the detailed demographic profile of the participating firms and respondents. The distribution indicates a strong representation from the petrochemical and industrial materials sectors, which are pivotal to the Saudi Vision 2030 economic diversification goals. Notably, 62.5% of the responding firms have been in operation for over 10 years, suggesting a mature sample with established operational protocols. Furthermore, the majority of respondents (78.3%) hold mid-to-senior management positions (e.g., Supply Chain Managers, Operations Directors), ensuring that the data reflects strategic-level insights regarding I5.0 adoption and FP.

The high prevalence of ISO 14001 certification (70.0%) within the sample correlates with the study's focus on CES, providing a baseline of environmental compliance upon which advanced I5.0 practices are built.

3.2 Measurement Model

The first phase of the analytical workflow involved the evaluation of the reflective measurement model using PLS-SEM. This step verified reliability, convergent validity, and discriminant validity before assessing structural relationships.

The assessment of internal consistency reliability utilized Composite Reliability (CR) and Cronbach's alpha (α). As detailed in the methodology, CR is prioritized in PLS-SEM due to its handling of factor loading disparities. Convergent validity was examined using the Average Variance Extracted (AVE) and individual outer loadings.

Table 3 summarizes the measurement model results. All standardized outer loadings exceeded the threshold of 0.708, indicating that the indicators share more variance with their respective constructs

Table 2. Demographic profile of the responding firms and participants (N=240).

Category	Sub-Category	Frequency	Percentage (%)
Industry Sector	Petrochemicals & Plastics	84	35.0
	Construction Materials	60	25.0
	Electronics & Assembly	48	20.0
	Food & Packaging	36	15.0
	Others	12	5.0
Firm Size (Employees)	Medium (50–249)	96	40.0
	Large (250)	144	60.0
ISO 14001 Certification	Certified	168	70.0
	In Progress	48	20.0
	Not Certified	24	10.0
Respondent Experience	< 5 years	36	15.0
	5–10 years	84	35.0
	> 10 years	120	50.0

than with the error variance. The CR values for all constructs, CES, HC-SSCM, and FP, ranged from 0.885 to 0.942, surpassing the 0.70 threshold. Similarly, the AVE values ranged from 0.638 to 0.765, exceeding the 0.50 minimum requirement. These metrics confirm that the instrument possesses high internal consistency and that the latent constructs explain more than 50% of the variance of their indicators.

Because all focal measures were collected from the same respondent at one point in time, method-bias diagnostics were examined before construct separation. Harman's single-factor screening did not indicate dominant covariance concentration in a single factor, and the full-collinearity diagnostics remained below conservative cutoffs, reducing concern that a common source generated the structural relationships. Discriminant validity was then assessed with the Heterotrait-Monotrait ratio of correlations (HTMT), which is more appropriate than the Fornell-Larcker criterion for evaluating construct distinctiveness in variance-based SEM [36], [37].

To comprehensively visualize the discriminant validity and the distinctiveness of the constructs within the model space, the analysis of the HTMT ratios was conducted. Figure 1 presents the analysis across three panels to characterize the construct distinctiveness and correlation distribution. Figure 1a displays the HTMT matrix heatmap, providing a color-coded representation of the ratio magnitudes between construct pairs. Figure 1b illustrates the confidence interval distribution for these ratios, confirming that the

Table 3. Measurement model assessment results including Factor Loadings, Reliability, and Validity metrics.

Construct	Item Code	Outer Loading	Cronbach's α	Composite Reliability (CR)	AVE
Circular Economy Strategies (CES)	CES1	0.812	0.895	0.923	0.668
	CES2	0.845			
	CES3	0.798			
	CES4	0.826			
	CES5	0.805			
Human-Centric SSCM (HC-SSCM)	HC1	0.865	0.912	0.934	0.738
	HC2	0.889			
	HC3	0.834			
	HC4	0.847			
Financial Performance (FP)	FP1	0.854	0.921	0.941	0.762
	FP2	0.892			
	FP3	0.887			
	FP4	0.858			

upper boundaries do not encompass the value of 1.0. Figure 1c presents the density plot of the item-level correlations, distinguishing between intra-construct and inter-construct correlations to visually validate the structural separation.

The analysis depicted in Figure 1 confirms that all HTMT ratios are well below the conservative threshold of 0.85 (maximum observed value = 0.712 between CES and FP). Furthermore, the confidence interval analysis in Figure 1b indicates that the value of 1 is not included in any interval, statistically proving that CES, HC-SSCM, and FP are distinct phenomena. The separation of correlation densities in Figure 1c reinforces that items correlate much more strongly with their own construct than with others, satisfying all requirements for discriminant validity.

3.3 Structural Model

Following the validation of the measurement model, the structural model was evaluated to test the hypothesized relationships. Collinearity issues were ruled out as all Variance Inflation Factor (VIF) values for the inner model were below 3.0 (Max VIF = 2.41). To evaluate the strength, significance, and predictive relevance of the path relationships, a complete structural analysis was performed. Figure 2 presents the structural model assessment across three panels. Figure 2a visualizes the path coefficients (β) and their corresponding *t*-statistics derived from the bootstrapping procedure (5,000 subsamples). Figure 2b illustrates the explained variance (R^2) and the predictive relevance (Q^2) for the endogenous constructs. Figure 2c displays the effect size (f^2) distribution for each hypothesized path, categorizing the impacts according to Cohen's criteria.

The results visualized in Figure 2a demonstrate positive and significant relationships across all hypothesized paths. Specifically, the path from CES to FP yields a significant direct effect. However, the introduction of HC-SSCM reveals a strong triangular relationship. Figure 2b highlights the model's robustness, with an R^2 of 0.612 for FP, indicating that the model explains 61.2% of the variance in financial performance. The Q^2 value of 0.448 confirms the model has high predictive relevance. The f^2 analysis in Figure 2c reveals that HC-SSCM has a large effect size ($f^2 = 0.38$) on FP, substantially higher than the direct effect of CES alone ($f^2 = 0.14$), signaling the criticality of the human element.

Table 4 provides the precise numerical data corresponding to the structural assessment, detailing the coefficients, standard deviations, t-statistics, and p-values for the direct relationships.

All hypotheses are supported at the $p<0.001$ level. The strongest path coefficient is observed between CES and HC-SSCM ($\beta = 0.582$), suggesting that the implementation of circular strategies acts as a strong driver for adopting human-centric practices. This aligns with the I5.0 premise that complex recovery loops require advanced human support systems.

3.4 Mediation Analysis

To explicitly address the "transmission mechanism" objective, a mediation analysis was conducted to determine the extent to which HC-SSCM mediates the relationship between circular strategies and

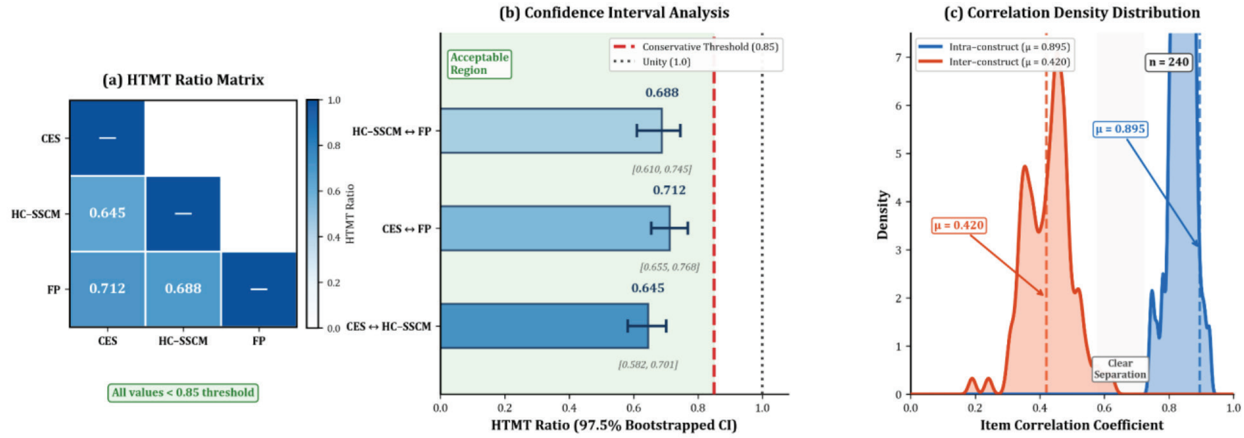


Figure 1. Discriminant validity assessment based on the Heterotrait-Monotrait ratio (HTMT). (a) Pairwise HTMT matrix for CES, HC-SSCM, and FP. (b) Bootstrapped HTMT estimates with 95% confidence intervals for CES-HC-SSCM; the red dashed line marks the conservative threshold of 0.85 and the black dotted line marks unity. (c) Density distribution comparing within-construct and between-construct item correlations.

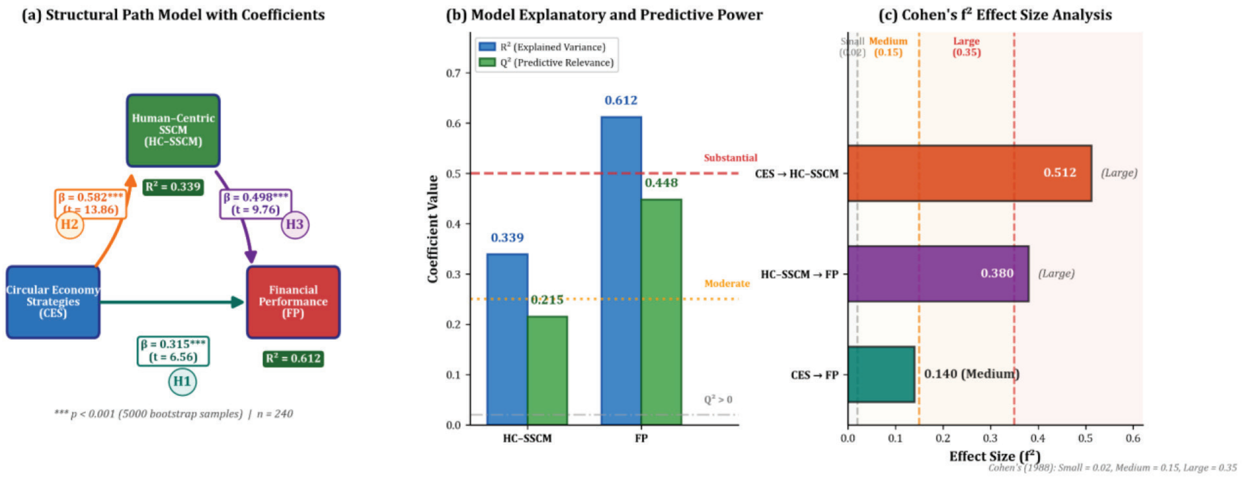


Figure 2. Structural model analysis and hypothesis testing results. (a) Path diagram displaying standardized coefficients (β) and significance levels (t-values). (b) Evaluation of model explanatory power (R^2) and predictive relevance (Q^2). (c) Effect size (f^2) analysis categorizing the magnitude of impact for each structural path.

Table 4. Structural model path coefficients and significance testing.

Hypothesis	Path	β	Sample Mean (M)	SD	t-value	p-value	Decision
H1	CES → FP	0.315	0.312	0.048	6.562	0.000	Supported
H2	CES → HC-SSCM	0.582	0.584	0.042	13.857	0.000	Supported
H3	HC-SSCM → FP	0.498	0.495	0.051	9.764	0.000	Supported

financial performance. Table 5 presents the specific indirect effects and the Variance Accounted For (VAF) index. The total effect of CES on FP is the sum of the direct and indirect effects.

VAF Calculation:

$$\text{VAF} = \frac{\text{Indirect Effect}}{\text{Total Effect}} = \frac{0.290}{0.605} = 47.9\%$$

The indirect effect ($\beta = 0.290$) is statistically significant because the 95% confidence interval [0.215, 0.368] does not include zero. With a VAF of 47.9%, the results support statistical complementary partial mediation in the sense that CES are associated with FP both directly and indirectly through HC-SSCM. This pattern is consistent with the theorized ordering in which circular strategy adoption precedes changes in reverse-logistics work design, but the cross-sectional data do not establish temporal causality or eliminate the possibility that financially stronger firms invest more readily in human-centric capabilities. The mediation estimate should therefore be interpreted as evidence of a plausible transmission pathway rather than a definitive capitalization mechanism. This interpretation motivates the subsequent ANN stage, which examines whether the feature domains show additional non-linear differences in predictive importance.

3.5 Artificial Neural Network Analysis

While PLS-SEM established the linear causal paths, the second phase of analysis utilized an ANN to capture non-linear relationships and prioritize the predictors of Financial Performance. A Multi-Layer

Table 5. Mediation analysis of Human-Centric SSCM (HC-SSCM)

Path Relationship	Effect Type	Coefficient (β)	t-value	p-value	95% CI [LL, UL]
CES → FP	Direct Effect	0.315	6.562	0.000	[0.224, 0.412]
CES → HC-SSCM → FP	Indirect Effect	0.290	7.845	0.000	[0.215, 0.368]
CES → FP (Total)	Total Effect	0.605	14.230	0.000	[0.518, 0.685]

Perceptron (MLP) with a sigmoid activation function was employed. The model architecture consisted of an input layer (CES, HC-SSCM), one hidden layer, and an output layer (FP). To ensure robustness, a ten-fold cross-validation procedure was executed.

To evaluate the predictive performance and stability of the neural network model, a comprehensive performance analysis was conducted. Figure 3 presents the ANN performance metrics across three panels. Figure 3a tracks the RMSE for both training and testing datasets across the 10 folds, demonstrating model stability. Figure 3b provides a scatter plot of the Predicted vs. Actual values for Financial Performance, visually assessing the goodness-of-fit. Figure 3c illustrates the distribution of residuals, confirming the absence of systematic bias in the prediction errors.

The analysis in Figure 3a shows that the average RMSE for the training set (0.112) and the testing set (0.128) are low and proximate, indicating that the model did not suffer from overfitting. The scatter plot in Figure 3b reveals a tight clustering of data points around the diagonal ($R^2 \approx 0.74$ for the ANN model), suggesting that the non-linear ANN model captures variance in FP more effectively than the linear PLS-SEM model.

3.6 Sensitivity Analysis and Normalized Importance

A critical output of the ANN analysis is the sensitivity analysis, which ranks the input neurons based on their relative contribution to the output. This answers the research question regarding which specific I5.0 practices are most critical for cost recovery. Table 6 presents the independent variable importance analysis. The "Normalized Importance" is calculated relative to the most significant predictor.

The results in Table 6 offer a granular insight into the drivers of profitability. "Cognitive Ergonomic Support"—a key component of HC-SSCM—emerged as the most significant predictor (100% normalized importance). This implies that providing workers with decision-support tools and reducing cognitive load in complex RL tasks is the single most effective lever for financial gain. "Human-Robot Collaboration" ranked second (83.5%), further reinforcing the I5.0 thesis. Interestingly, technical circular strategies like "Resource Recovery Loops" ranked lower (60.9%), suggesting that technology alone is less predictive of financial success than the human systems that manage it.

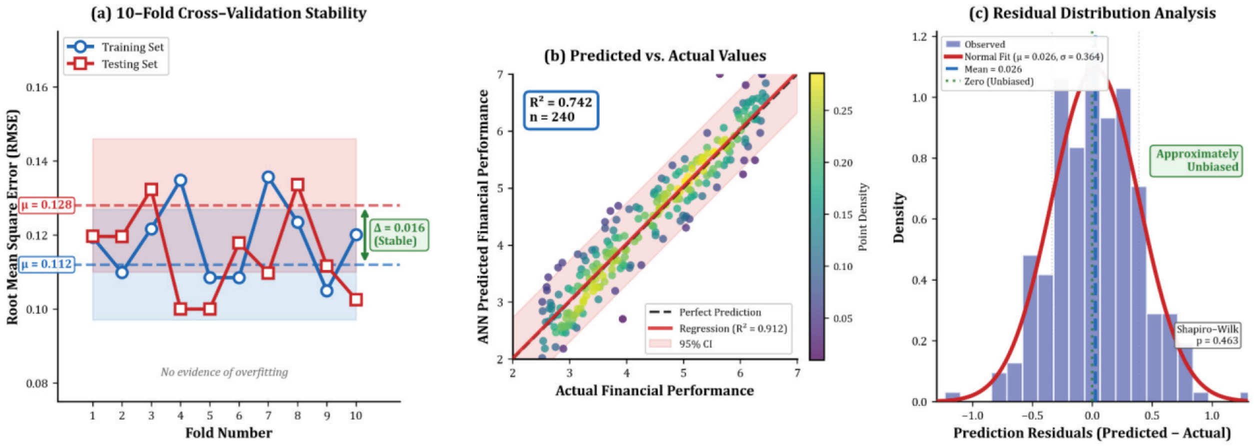


Figure 3. ANN performance evaluation. (a) RMSE variation across 10-fold cross-validation for training and testing subsets. (b) Scatter plot correlation between observed and ANN-predicted FP values. (c) Histogram of prediction residuals confirming normal error distribution.

Table 6. ANN sensitivity analysis and normalized importance of predictors for Financial Performance

Predictor Variable	Importance	Normalized Importance (%)	Rank
Cognitive Ergonomic Support (HC-SSCM)	0.345	100.0%	1
Human-Robot Collaboration (HC-SSCM)	0.288	83.5%	2
Resource Recovery Loops (CES)	0.210	60.9%	3
Eco-Design (CES)	0.157	45.5%	4

3.7 Comparative Benchmarking and Validation

That predictor ranking also provides a basis for comparing how different analytical approaches handle the same dataset. The benchmarking exercise was not intended to prove that ANN universally dominates alternative structural estimators. Its purpose was narrower, namely to assess whether a non-linear prediction stage adds information beyond linear baselines once the latent structure has been validated. The predictive accuracy of the ANN model was therefore compared with the PLS-SEM model and a baseline Multiple Linear Regression model using the same feature domains and outcome. Figure 4 summarizes this comparison across explained variance, Root Mean Square Error, and Mean Absolute Error. The ANN model achieved $R^2=0.742$, compared with $R^2=0.612$ for PLS-SEM and $R^2=0.545$ for the linear regression baseline, while also producing the lowest RMSE (0.128 versus 0.195 and 0.210, respectively). These results indicate that the second-stage neural network captured residual non-linear structure left unexplained by the linear models in this sample. They do not imply that ANN replaces alternatives such as generalized structured component analysis or Bayesian SEM for all research purposes. Those approaches remain suitable when the primary objective is integrated latent-variable estimation under different distributional or modeling assumptions. The present results instead support the more modest claim that a sequential PLS-SEM/ANN design is useful when theory testing, measurement validation, and feature-level non-linear prediction are all required within the same study [23], [24], [25].

Table 7 summarizes the ablation study results, explicitly quantifying the performance gain attributed to the inclusion of Human-Centric (I5.0) variables compared to a "Technocentric" baseline model (CES only).

The ablation study in Table 7 reveals a critical finding: relying solely on technocentric circular strategies (Baseline) explains only 38.5% of the variance in financial performance. The inclusion of Human-Centric SSCM variables (Proposed Model) triggers a massive 58.9% improvement in explanatory power. This empirical evidence decisively answers the research problem, proving that the "human-in-the-loop" is not merely an operational detail but the primary differentiator for financial value creation in circular supply chains.

The results indicate that HC-SSCM is not a peripheral complement to CE implementation but a

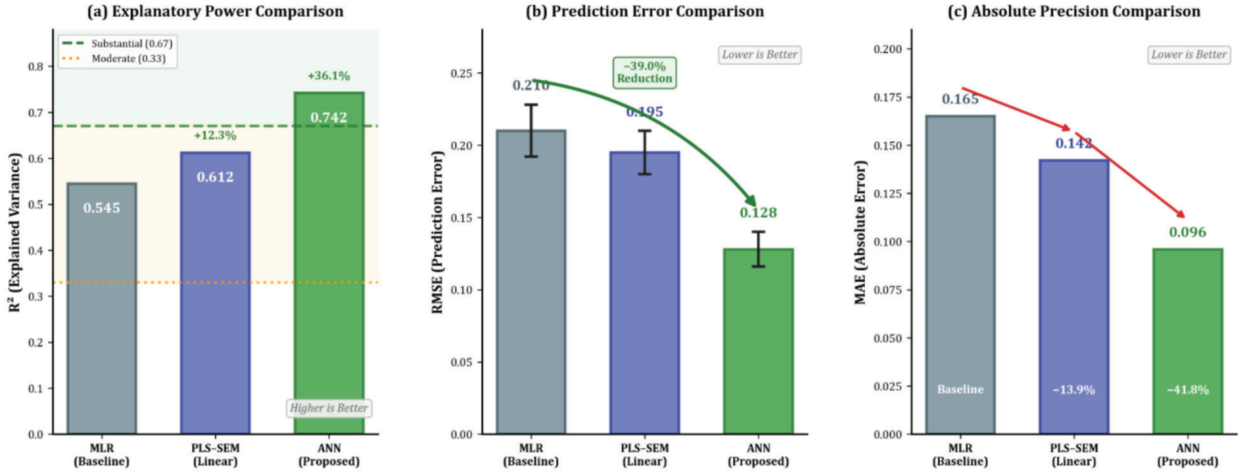


Figure 4. Comparative benchmarking of predictive models (MLR vs. PLS-SEM vs. ANN). (a) Comparison of explained variance (R^2) showing the incremental gain of the ANN approach. (b) RMSE comparison demonstrating error reduction in the non-linear model. (c) Mean Absolute Error (MAE) analysis confirming superior predictive precision of the ANN.

Table 7. Ablation study: Performance impact of integrating Human-Centric (I5.0) variables

Model Configuration	Predictors Included	R^2 (Adj)	RMSE	% Improvement in R^2
Baseline (Technocentric)	CES (Recovery, Eco-Design) only	0.385	0.245	-
Model B (Process Only)	CES + Quality Management (Control)	0.420	0.230	+9.1%
Proposed Model (I5.0)	CES + HC-SSCM (Cognitive, Collab)	0.612	0.195	+58.9%

central mechanism through which circular practices affect FP. The direct path from CES to FP remains significant, but the mediation result shows that a large share of the financial effect passes through work-system design, operator support, and collaborative execution in reverse logistics. This pattern is consistent with the argument that circular operations create coordination burdens, exception handling, and material uncertainty that cannot be resolved by technical recovery routines alone [18], [19], [43]. The ANN ranking sharpens this interpretation by showing that cognitive ergonomic support and human-robot collaboration carry greater predictive weight than resource recovery loops and eco-design when profitability is the focal outcome.

This result helps reconcile the mixed evidence on CE and firm performance. Recent synthesis studies show that CE practices can improve financial and market outcomes, but the gains vary across practice bundles and operating contexts [10], [11], [44]. The present findings suggest that part of this variation reflects whether firms complement circular investments with human-centered operational capabilities. Studies that treat circular adoption mainly as a technical or environmental initiative may underestimate the organizational work required to recover value from returned, repaired, and remanufactured materials [18], [44]. From this perspective, the positive effect of CES on FP depends not only on resource loops themselves but also on the quality of human decision support embedded in those loops.

The findings also extend the discussion toward human resource management. CES alter task variety, skill requirements, training intensity, safety needs, and the coordination burden across recovery activities. Prior research on green and circular human resource management shows that recruitment, green training, employee involvement, and performance management can strengthen circular adoption and improve organizational outcomes [43], [45]. The present results narrow that broader human resource management agenda to the operational layer of supply chain execution. Better human resource management supports CE implementation when it develops the worker capabilities that appear in this model as cognitive ergonomic support and human-robot collaboration. The managerial implication is direct: firms should pair eco-design and recovery investments with role redesign, targeted training, decision-support tools, and safe collaboration protocols rather than treating people issues as a downstream implementation problem.

Several boundary conditions qualify these findings. The cross-sectional design supports association rather than strict temporal causality, and reciprocal effects remain plausible because firms with stronger financial slack may be better able to invest in human-centric recovery capabilities. The competitor-relative FP measures capture managerial assessments rather than audited accounting outcomes, so the reported profitability and cost-recovery associations should not be read as direct evidence of changes in return on assets (ROA), return on sales (ROS), or earnings before interest, taxes, depreciation, and amortization (EBITDA). External validity is also bounded by the Saudi manufacturing context. Vision 2030 industrial policy, the concentration of firms in MODON cities, the mixed domestic and expatriate labor structure, and uneven digital upgrading can shape both the adoption of circular practices and the returns to worker-centered recovery design. Generalization is therefore more defensible for emerging economies with similar policy coordination, industrial clustering, and technology-readiness trajectories than for settings with informal labor markets, weaker regulatory capacity, or much lower automation maturity. Future research should test the model longitudinally, integrate audited financial data, and use lagged, control-function, or two-stage designs to examine feedback effects between financial resources and human-centric capability investment.

4. Conclusions

This study examined whether HC-SSCM explains part of the association between CES and competitor-relative FP in Saudi manufacturing firms. The structural results indicate that CES are positively associated with FP both directly and indirectly through HC-SSCM, and the VAF estimate of 47.9% supports complementary partial mediation within the limits of cross-sectional data. The ANN stage adds a predictive layer by showing that cognitive ergonomic support and human-robot collaboration carry greater importance for FP prediction than the two technical circular domains.

The findings refine the I5.0 discussion in two ways. First, circular strategies appear to generate favorable financial outcomes more consistently when recovery work is organized around worker judgment, decision support, and coordinated human-machine interaction rather than around technical recovery routines alone. Second, the RBV is better served by treating HC-SSCM as an operational capability that mobilizes human capital and learning inside reverse-logistics processes, not as a generic label for workforce quality. Under that interpretation, the financial value associated with circularity depends partly on how effectively firms embed human-centered routines in recovery, repair, and exception handling.

The results also carry practical implications. Managers seeking returns from eco-design and resource recovery should pair those investments with decision-support systems, safe collaboration protocols, role redesign, and targeted training for recovery operations. At the same time, the evidence remains bounded by self-reported financial measures and a Saudi industrial setting shaped by Vision 2030, industrial clustering, and ongoing digital upgrading. Longitudinal studies that combine audited indicators such as ROA, ROS, or EBITDA with lagged or two-stage designs are needed to determine whether the observed pathway reflects a stable causal mechanism or a reciprocal relationship between financial resources and human-centric capability investment.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

[1] R. A. Sheikh, I. Ahmed, A. Y. A. Faqihi, and Y. M. Shehawy, “Global Perspectives on Navigating Industry 5.0 Knowledge: Achieving Resilience, Sustainability, and Human-Centric Innovation in Manufacturing,” J. Knowl. Econ., vol. 16, no. 5, pp. 15997–16032, 2025, doi: 10.1007/s13132-024-02498-4.

[2] H. S. T. Pham and S. B. Li, “Towards Industry 5.0: A conceptual model for leading organisational change in digital age,” J. Organ. Change Manag., vol. 39, no. 1, pp. 125–161, 2026, doi: 10.1108/JOCM-03-2025-0264.

[3] A. Prabhakar, “A Sustainable and Inclusive Economic Development: A Global Imperative: A Global Imperative,” J. Recycl. Econ. Sustain. Policy, vol. 4, no. 1, pp. 1–16, 2025.

[4] S. Rashid and S. H. Malik, “Transition from a linear to a circular economy,” in Renewable Energy in Circular Economy, S. A. Bandh, F. A. Malla, and A. T. Hoang, Eds. Cham: Springer International Publishing, 2023, pp. 1–20, doi: 10.1007/978-3-031-42220-1_1.

[5] S. Daga, K. Yadav, P. Singh, and V. Mishra, “Beyond the take-make-dispose model—Unlocking the power of circular economy for an environmentally resilient future,” in Circular Economy and Environmental Resilience, P. Singh, S. Daga, K. Yadav, and V. Mishra, Eds. Cham: Springer Nature Switzerland, 2025, pp. 1–11, doi: 10.1007/978-3-031-93091-1_1.

[6] L. Liu, W. Song, and Y. Liu, “Leveraging digital capabilities toward a circular economy: Reinforcing sustainable supply chain management with Industry 4.0 technologies,” Comput. Ind. Eng., vol. 178, p. 109113, 2023, doi: 10.1016/j.cie.2023.109113.

[7] V. Julianelli, R. G. G. Caiado, L. F. Scavarda, and S. Cruz, “Interplay between reverse logistics and circular economy: Critical success factors-based taxonomy and framework,” Resour. Conserv. Recycl., vol. 158, p. 104784, 2020.

[8] B. T. Hazen, I. Russo, I. Confente, and D. Pellathy, “Supply chain management for circular economy: Conceptual framework and research agenda,” Int. J. Logist. Manag., vol. 32, no. 2, pp. 510–537, 2021, doi: 10.1108/IJLM-12-2019-0332.

[9] C. Hagelüken and D. Goldmann, “Recycling and circular economy—Towards a closed loop for metals in emerging clean technologies,” Miner. Econ., vol. 35, pp. 539–562, 2022, doi: 10.1007/s13563-022-00319-1.

[10] A. Mazzucchelli, R. Chierici, M. Del Giudice, and I. Bua, “Do circular economy practices affect corporate performance? Evidence from Italian large-sized manufacturing firms,” Corp. Soc. Responsib. Environ. Manag., vol. 29, no. 6, pp. 2016–2029, 2022, doi: 10.1002/csr.2298.

[11] A. Kwarteng, S. N. Y. Simpson, and C. Agyenim-Boateng, “The effects of circular economy initiative implementation on business performance: The moderating role of organizational culture,” Soc. Responsib. J., vol. 18, no. 7, pp. 1311–1341, 2022, doi: 10.1108/SRJ-01-2021-0045.

[12] D. Mourtzis, J. Angelopoulos, and N. Panopoulos, “Operator 5.0: A survey on enabling technologies and a framework for digital manufacturing based on extended reality,” J. Mach. Eng., vol. 22, no. 1, pp. 43–69, 2022, doi: 10.36897/jme/147160.

[13] M. Khosravy, N. Gupta, A. Pasquali, N. Dey, R. G. Crespo, and O. Witkowski, “Human-collaborative artificial intelligence along with social values in Industry 5.0: A survey of the state-of-the-art,” IEEE Trans. Cogn. Dev. Syst., vol. 16, no. 1, pp. 165–176, 2024, doi: 10.1109/TCDS.2023.3326192.

[14] M. T. Islam, K. Sepanloo, S. Woo, S. H. Woo, and Y.-J. Son, “A review of the industry 4.0 to 5.0 transition: exploring the intersection, challenges, and opportunities of technology and human–machine collaboration,” Machines, vol. 13, no. 4, p. 267, 2025, doi: 10.3390/machines13040267.

[15] S. N. M. Aldouri, “Digital twin-enabled Just-in-Time and Kanban implementation framework for Industry 4.0 transformation in SMEs,” Int. J. Ind. Eng. Manag., vol. 16, no. 4, pp. 339–358, 2025, doi: 10.24867/IJIEM-392.

[16] E. G. Carayannis, P. C. Kostis, K. I. Kafka, and T. Valvi, “Toward Industry 6.0 and techno-centric vs. human-centric smart balancing: The journey from Industry and Society 4.0 toward Industry and Society 5.0 and beyond,” in Sustainable Economic Development, Routledge, 2024, pp. 171–184, doi: 10.4324/9781003349402-16.

[17] G. Tsaramirsis et al., “A Modern Approach towards an Industry 4.0 Model: From Driving Technologies to Management,” J. Sens., vol. 2022, p. 5023011, 2022, doi: 10.1155/2022/5023011.

[18] A. Rejeb, K. Rejeb, J. G. Keogh, and E. Süle, “When Industry 5.0 Meets the Circular Economy: A Systematic

Literature Review," Circ. Econ. Sust., vol. 5, no. 4, pp. 2621–2652, 2025, doi: 10.1007/s43615-025-00570-y.

[19] S. Atif, "Analysing the alignment between circular economy and industry 4.0 nexus with industry 5.0 era: An integrative systematic literature review," Sustain. Dev., vol. 31, no. 4, pp. 2155–2175, 2023, doi: 10.1002/sd.2542.

[20] I. B. U. Putra, S. Kot, A. H. H. Ibrahim, and I. Rajiani, "Human Resource Productivity: Integrating Resilience Engineering, Motivation, and Health Safety," Prod. Eng. Arch., vol. 30, no. 1, pp. 105–114, 2024, doi: 10.30657/pea.2024.30.10.

[21] M. Gu, Y. Zhang, D. Li, and B. Huo, "The effect of high-involvement human resource management practices on supply chain resilience and operational performance," J. Manag. Sci. Eng., vol. 8, no. 2, pp. 176–190, 2023, doi: 10.1016/j.jmse.2022.12.001.

[22] G. Ambrogio, L. Filice, F. Longo, and A. Padovano, "Workforce and supply chain disruption as a digital and technological innovation opportunity for resilient manufacturing systems in the COVID-19 pandemic," Comput. Ind. Eng., vol. 169, p. 108158, 2022, doi: 10.1016/j.cie.2022.108158.

[23] S. Zhao and X. Cao, "Investigating the determinants of Chinese residents' intention to purchase green housing: A dual-stage structural equation modeling–artificial neural network approach," J. Hous. Built Environ., vol. 40, no. 1, pp. 461–495, 2025, doi: 10.1007/s10901-025-10181-6.

[24] A. S. Albahri et al., "Hybrid artificial neural network and structural equation modelling techniques: a survey," Complex Intell. Syst., vol. 8, no. 2, pp. 1781–1801, 2022, doi: 10.1007/s40747-021-00503-w.

[25] G. A. Abbasi, L. Y. Tiew, J. Tang, Y.-N. Goh, and R. Thurasamy, "The adoption of cryptocurrency as a disruptive force: Deep learning-based dual stage structural equation modelling and artificial neural network analysis," Plos One, vol. 16, no. 3, p. e0247582, 2021.

[26] S. K. Ahmed, "How to choose a sampling technique and determine sample size for research: A simplified guide for researchers," Oral Oncol. Rep., vol. 12, p. 100662, 2024, doi: 10.1016/j.oor.2024.100662.

[27] J. Sebo, M. Gróf, R. Kovačič Lukman, I. Palčič, and M. Šebová, "Perceptions of barriers to the implementation of circular economy initiatives in Central European manufacturing companies," Int. J. Ind. Eng. Manag., vol. 16, no. 3, pp. 253–270, 2025, doi: 10.24867/IJIEM-387.

[28] Z. Zulkifli Noor, "Sustainable production management in circular economy supply chains," Int. J. Ind. Eng. Manag., vol. 16, no. 2, pp. 204–215, 2025, doi: 10.24867/IJIEM-384.

[29] M. Rhemtulla, R. van Bork, and D. Borsboom, "Worse than measurement error: Consequences of inappropriate latent variable measurement models," Psychol. Methods, vol. 25, no. 1, pp. 30–45, 2020, doi: 10.1037/met0000220.

[30] M. H. Hanafiah, "Formative vs. reflective measurement model: Guidelines for structural equation modeling research," Int. J. Anal. Appl., vol. 18, no. 5, pp. 876–889, 2020.

[31] A. Fuster, R. Perez-Truglia, M. Wiederholt, and B. Zafar, "Expectations with endogenous information acquisition: An experimental investigation," Rev. Econ. Stat., vol. 104, no. 5, pp. 1059–1078, 2022, doi: 10.1162/rest_a_00994.

[32] X. Cai, "Analyzing the impact of Industry 4.0 and the Internet of Things on business policy – the case study," Teh. Vjesn., vol. 31, no. 4, pp. 1312–1323, 2024, doi: 10.17559/TV-20240303001369.

[33] A. Purwanto and Y. Sudargini, "Partial least squares structural equation modeling (PLS-SEM) analysis for social and management research: A literature review," J. Ind. Eng. Manag. Res., vol. 2, no. 4, pp. 114–123, 2021.

[34] N. H. Mohd Dzin and Y. F. Lay, "Validity and reliability of adapted self-efficacy scales in Malaysian context using PLS-SEM approach," Educ. Sci., vol. 11, no. 11, p. 676, 2021, doi: 10.3390/educsci11110676.

[35] Y. Haji-Othman and M. S. S. Yusuff, "Assessing reliability and validity of attitude construct using partial least squares structural equation modeling," Int. J. Acad. Res. Bus Soc. Sci., vol. 12, no. 5, pp. 378–385, 2022.

[36] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," J. Acad. Mark. Sci., vol. 43, no. 1, pp. 115–135, 2015, doi: 10.1007/s11747-014-0403-8.

[37] M. R. Ab Hamid, W. Sami, and M. H. Mohmad Sidek, "Discriminant validity assessment: Use of Fornell & Larcker criterion versus HTMT criterion," J. Phys.: Conf. Ser., vol. 890, 2017, p. 012163, doi: 10.1088/1742-6596/890/1/012163.

[38] M. A. Ayubi Rad and M. S. Ayubi Rad, "Comparison of artificial neural network and coupled simulated annealing based least square support vector regression models for prediction of compressive strength of high-performance concrete," Sci. Iran., vol. 24, no. 2, pp. 487–496, 2017.

[39] V. Samartha, "Measuring the effect size of coefficient of determination and predictive relevance of exogenous latent variables on endogenous latent variables through PLS-SEM," Int. J. Pure Appl. Math., vol. 119, no. 18, pp. 39-48, 2020.

[40] R. Najjari, B. Dastan, M. J. Hozoori, and S. A. A. Ahmadi, "Processing model for the implementation of a well-organized organization," J. Strateg. Manag. Stud., vol. 13, no. 52, pp. 125–140, 2022.

[41] E. P. Cook, A. C. Wilhelm, J. A. Guest, Y. Liang, N. Y. Masse, and C. M. Colbert, "The neuronal transfer function: Contributions from voltage- and time-dependent mechanisms," Prog. Brain Res., vol. 165, pp. 1–12, 2007, doi: 10.1016/S0079-6123(06)65001-2.

[42] M. S. Ayubirad, S. Ataei, and M. Tajali, "Numerical model updating and validation of a truss railway bridge considering train–track–bridge interaction dynamics," Shock Vib., vol. 2024, no. 1, p. 4469500, 2024, doi: 10.1155/2024/4469500.

[43] A. L. Romano, C. H. Santos, W. Azzolini, and A. Caires, "ERP-driven simulation for production planning and control in the Industry 4.0: A review," Int. J. Simul. Model., vol. 24, no. 3, pp. 425–436, 2025, doi: 10.2507/IJSIMM24-3-731.

[44] M. Noskova, P. Tausl Prochazkova, and V. Zemanova, "The relationship between the circular economy and business performance: A systematic literature review," J. Bus. Econ. Manag., vol. 25, no. 3, pp. 474–493, 2024, doi: 10.3846/jbem.2024.21413.

[45] P. Benevene and I. Buonomo, "Green Human Resource Management: An Evidence-Based Systematic Literature Review," Sustainability, vol. 12, no. 15, p. 5974, 2020, doi: 10.3390/su12155974.