

Optimizing CSR Efficiency for Poverty Alleviation in Tourism-Based Development: Evidence from Indonesia

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ABSTRACT

This study addresses the gap between measuring the efficiency of tourism-based Corporate Social Responsibility (CSR) programs and explaining how that efficiency translates into poverty reduction. Using an integrated Data Envelopment Analysis (DEA) and Partial Least Squares Structural Equation Modeling (PLS-SEM) framework, the study analyzed 87 tourism-based CSR programs and survey data from 285 stakeholders in Indonesia. DEA (BCC, output-oriented, VRS) reveals an average technical efficiency of 78.34%, with programs classified under Increasing (43.7%), Constant (20.7%), and Decreasing (35.6%) Returns to Scale. The efficiency-outcome link is strongest among Increasing>Returns-to-Scale programs ($\beta = 0.102$) and weakest among Decreasing>Returns-to-Scale programs ($\beta = 0.071$), despite the latter receiving the highest average funding. PLS-SEM confirms all seven hypothesized paths, with SDG Implementation Effectiveness showing the strongest direct effect on Poverty Alleviation Outcomes ($\beta = 0.421$, $p < .001$) and mediating over half of DEA efficiency's total effect on poverty outcomes. Efficiency and social mission are complementary, and Returns-to-Scale classification is a critical contingency for CSR portfolio design. The study offers a scale-sensitive portfolio classification and policy guidance for channeling tourism-based CSR toward Indonesia's poverty-reduction and SDGs agenda.

KEYWORDS

CSR
Data envelopment analysis
Poverty alleviation
SDGs
Tourism-based development

INTRODUCTION

Corporate social responsibility (CSR) programs linked to tourism development are widely promoted as instruments for poverty alleviation, yet their measurable impact in developing economies remains inconsistent. In Indonesia, where nearly 26 million people remained below the poverty line in 2023 (BPS, 2023), many tourism-based CSR initiatives continue to face inefficient resource allocation and an unclear link between program inputs and poverty outcomes (Muthuri & Gilbert, 2011), despite their recognized contribution to local livelihoods and cultural preservation (Hampton & Jeyacheya, 2020). Comparable inconsistency has recently been documented outside Indonesia as well: in Lebanon, tourism-driven development has been shown to translate unevenly into poverty reduction depending on how cultural preservation, income growth, and community empowerment are jointly

managed (El Zein et al., 2025), while spatial Data Envelopment Analysis (DEA) evidence from China confirms that tourism-linked poverty-alleviation efficiency can vary sharply even within a single province or corridor (Xiao et al., 2023; Zhang & Wu, 2024).

This gap partly reflects a methodological divide in the literature. Data Envelopment Analysis (DEA) can benchmark the relative technical efficiency of CSR programs but does not explain why some programs are more efficient than others, while Partial Least Squares Structural Equation Modeling (PLS-SEM) can test causal pathways among managerial and contextual factors but offers no direct measure of operational efficiency (Cook & Seiford, 2009; Liu et al., 2013). As a result, efficiency and effectiveness are typically evaluated in isolation, and the Sustainable Development Goals (SDGs) are more often treated as a reporting checklist than as an operational mechanism linking program design to outcomes (Scheyvens et al., 2016), even though tourism is explicitly positioned by the sector's own global body as a vehicle capable of contributing to all 17 SDGs when properly integrated into destination planning (UNWTO, 2017).

A recent systematic review of the tourism-poverty literature likewise concludes that most existing models remain fragmented across efficiency-oriented and mechanism-oriented traditions, with few studies formally testing how the two connect (Shah, 2025). This study, therefore, addresses the following research questions: (1) how can the efficiency of tourism-based CSR programs be measured and explained within a single analytical framework, and (2) what role do SDG-aligned practices play in converting that efficiency into poverty-reduction outcomes in Indonesia?

To answer these questions, the study develops and tests an integrated DEA-PLS-SEM framework using data from 87 tourism-based CSR programs and a survey of 285 stakeholders in Indonesia, offering three contributions. Methodologically, it shows how efficiency benchmarking (DEA) and causal-pathway testing (PLS-SEM) can be combined within a single program-level dataset (Creswell & Plano Clark, 2017; Staessens et al., 2019). Theoretically, it positions SDG implementation as a testable operational mediator between managerial practices and poverty outcomes rather than a normative backdrop (Porter & Kramer, 2011; Scheyvens et al., 2016). Practically, it derives a returns-to-scale-sensitive CSR portfolio strategy, offering differentiated guidance on which programs should be scaled up, standardized, or restructured (Banker et al., 1984).

LITERATURE REVIEW

CSR, Tourism Development, and Poverty Alleviation

The scholarly discourse on CSR has, over time, evolved from viewing corporate social initiatives primarily as acts of philanthropy to understanding them as potential instruments for strategic value creation (Porter & Kramer, 2011). The notion of “creating shared value” provides a useful theoretical lens, suggesting that addressing social needs and generating business value are not mutually exclusive. Empirical evidence from the hospitality sector supports this view, with CSR engagement shown to be positively associated with customer satisfaction among publicly traded hotel and restaurant firms (Lee & Heo, 2009). This perspective, in practice, offers a foundation for examining the efficiency of CSR activities. Within the tourism sector in developing countries like Indonesia, CSR initiatives are often expected to operate through multiple channels. These include direct mechanisms, such as providing employment and skills training, as well as more indirect pathways, like improving local infrastructure or fostering market linkages for community products (Ashley et al., 2007).

However, the observed impact of tourism-CSR programs on poverty is notably inconsistent. Literature points to factors contributing to more successful outcomes, including genuine community

involvement, long-term corporate commitment, and integration with local economic realities and national development priorities (Goodwin, 2016). Recent Indonesian evidence reinforces this: multi-stakeholder collaboration around tourism villages translates into durable local benefit only when CSR engagement is sustained rather than ad hoc (Hendrayani et al., 2025), and stakeholder commitment, attitude, and performance jointly—rather than any single actor's involvement—determine whether tourism-village development is sustained (Ferdian et al., 2024). While valuable, these qualitative and survey-based insights are difficult to compare systematically or optimize strategically across a program portfolio, leaving a gap for methodologies that translate these principles into quantifiable, comparable metrics—a gap that approaches like Data Envelopment Analysis (DEA) may be well-positioned to address (Wong et al., 2021).

Efficiency Measurement in CSR and Development Programs

Data Envelopment Analysis (DEA), since its introduction by Charnes et al. (1978), offers a way to assess the relative efficiency of decision-making units without imposing a strict functional form on the production process. The Banker-Charnes-Cooper (BCC) model further refines this by accommodating variable returns to scale, acknowledging that development programs may not operate at an optimal scale where inputs and outputs increase proportionally (Banker et al., 1984). While DEA has seen extensive application in sectors like healthcare and public administration, its use in evaluating CSR initiatives within tourism-based development remains relatively limited, with related applications typically confined to single-sector settings such as tourism poverty alleviation in ethnic regions of China (Lu et al., 2018; Yang et al., 2021). More recent DEA applications continue to confirm marked spatial and temporal heterogeneity in tourism-linked poverty-alleviation efficiency, whether examined across provinces (Xiao et al., 2023) or along multi-city tourism corridors using staged DEA designs (Zhang & Wu, 2024), underscoring the continued relevance of efficiency benchmarking to this field.

Beyond these sector-specific applications, a broader methodological issue remains. Recent discussions have highlighted the potential benefits of integrating DEA with Structural Equation Modeling (SEM), since the two methods address different questions: DEA measures how efficient a program is relative to its peers, identifying performance benchmarks, while SEM tests hypothesized causal relationships and mediation effects among constructs. Neither method alone fully captures both dimensions; DEA does not explain the causal drivers of efficiency, while SEM lacks an inherent mechanism for measuring relative efficiency frontiers (Liu et al., 2013). This is why an integrated approach seems promising: combining the two could allow researchers to identify which programs work best (DEA) and explore why they work (SEM), offering more comprehensive insights for improving performance.

Theoretical Framework and Hypotheses

The hypothesized relationships draw on four complementary theoretical perspectives, each of which grounds a specific set of paths in the model. First, the Resource-Based View (RBV) frames data-driven CSR management, tourism development quality, and community empowerment as strategic organizational resources that shape how effectively a program is implemented (Barney, 1991). Second, Stakeholder Theory explains why the quality of engagement with communities, government, and partners is expected to influence both SDG implementation and poverty outcomes, since alignment with stakeholder expectations affects how resources are converted into results (Freeman, 1984). Recent structural-equation evidence corroborates this pathway by showing that

community empowerment shapes sustainable tourism outcomes indirectly through local support rather than directly (Wani et al., 2024). Third, the Capability Approach directs attention to poverty alleviation as an expansion of substantive freedoms rather than income alone, justifying the use of a multidimensional Poverty Alleviation Outcomes construct (Sen, 1999), a framing consistent with more recent multidimensional treatments of tourism-linked poverty reduction in other emerging markets (El Zein et al., 2025). Finally, Institutional Theory situates SDG implementation within Indonesia's regulatory and normative environment, providing the rationale for treating SDG Implementation Effectiveness as an operational mediator rather than a background condition (Scott, 2008). This is consistent with recent institutional-theory evidence showing that multinational and domestic firms alike translate external normative and coercive pressures into internal SDG-aligned CSR practice (Diab & Stubbs, 2025; Zenda et al., 2025).

A clarification is warranted on how these SEM-based hypotheses relate to the DEA stage of the study. DEA produces a program-level technical efficiency score through non-parametric benchmarking; it identifies which programs are relatively efficient but is not designed to test why (Cook & Seiford, 2009). The hypotheses below, therefore, do not treat DEA outputs as SEM indicators. Instead, they model perceptual, stakeholder-reported constructs, namely data-driven management, tourism development quality, community empowerment, SDG implementation, and poverty alleviation outcomes, collected independently of the DEA input-output data. These SEM constructs represent plausible managerial and contextual antecedents and consequences of efficient program design (Staessens et al., 2019). The empirical link between the two stages, that is, whether programs with higher DEA efficiency scores also score higher on these SEM constructs, is not assumed but tested directly through the convergent-validity and regression analyses reported in the Integrated DEA-SEM Analysis section.

Stage 1: Determinants of SDG Implementation Effectiveness

The first set of hypotheses concerns the managerial and contextual factors that shape how effectively a program translates its activities into SDG-aligned practice.

H1: Data-driven CSR management positively influences SDG implementation effectiveness (Chen et al., 2018).

H2: Tourism development quality positively influences SDG implementation effectiveness (Goodwin, 2016).

H3: Community empowerment positively influences SDG implementation effectiveness (Mikkilineni & Brown, 2020; Wani et al., 2024).

Stage 2: Pathways to Poverty Alleviation Outcomes

The second set of hypotheses concerns how SDG implementation and the same three antecedents relate to poverty alleviation outcomes, allowing the model to distinguish an indirect, SDG-mediated pathway from direct effects.

H4: SDG implementation effectiveness positively influences poverty alleviation outcomes (Scheyvens et al., 2016; Giménez Espín et al., 2026).

H5: Data-driven CSR management positively influences poverty alleviation outcomes (Cook & Seiford, 2009).

H6: Tourism development quality positively influences poverty alleviation outcomes (Ashley et al., 2007).

H7: Community empowerment positively influences poverty alleviation outcomes (Mikkilineni & Brown, 2020).

In addition to these seven SEM-based hypotheses, the integrated analysis examines whether a program's Returns-to-Scale (RTS) classification, derived independently from the DEA stage, moderates the strength of the relationship between DEA efficiency scores and SEM-derived poverty alleviation outcomes. This moderation test is treated as a boundary condition on the integrated model rather than an additional SEM path, since RTS is a DEA-based classification and not a survey construct (Banker et al., 1984). Figure 1 presents the conceptual research model, including all hypothesized paths (H1–H7) and the RTS moderation as a boundary condition.

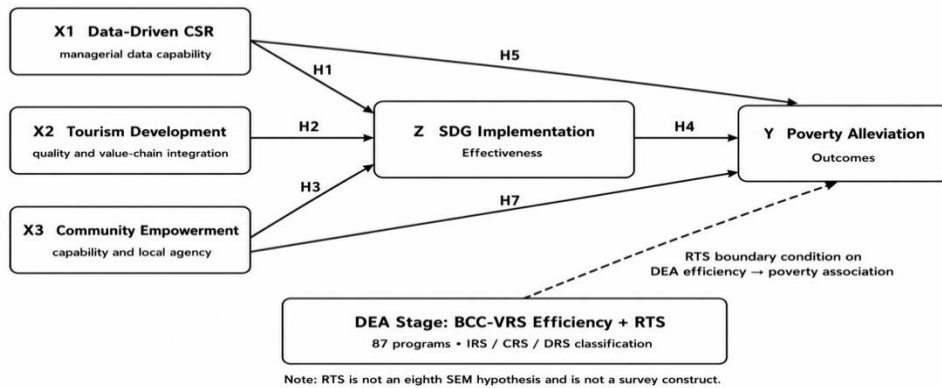


Figure 1. Conceptual Research Model with Hypothesized Paths (H1–H7) and Returns-to-Scale as a Boundary Condition

RESEARCH METHOD

Research Design

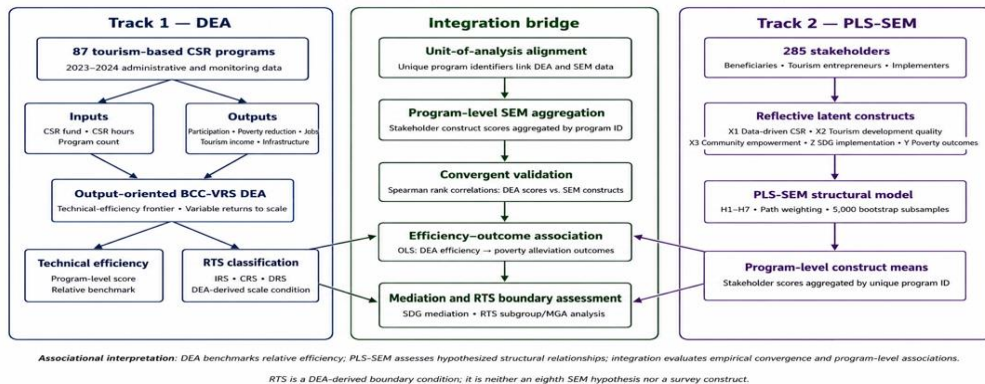


Figure 2. Methodological Procedure: Two-Stage DEA-PLS-SEM Integration Protocol

To address the research questions, this study adopted a sequential explanatory mixed-methods design, combining an initial quantitative phase of efficiency analysis (DEA) with a subsequent phase of causal path modeling (PLS-SEM). The design was informed by a pragmatist epistemological stance prioritizing methodological pluralism to yield actionable insights for assessing CSR program performance (Creswell & Plano Clark, 2017). The two-stage structure leveraged the distinct strengths of each method: Figure 2 illustrates the sequential procedure, showing how DEA efficiency

benchmarking integrates with PLS-SEM causal pathway testing. DEA provides relative, non-parametric efficiency benchmarking useful for comparing diverse programs without assuming a specific functional form (Cooper et al., 2007), while the PLS-SEM stage examines hypothesized causal relationships and latent constructs that might explain the efficiency scores and final outcomes (Hair et al., 2019).

Stage 1: Data Envelopment Analysis

Sample and Data Collection. The analysis in this stage was based on a sample of 87 tourism-based CSR programs. These programs were implemented by 17 major corporations operating in Indonesia, including both state-owned and private entities, during the period of 2023 to 2024. A purposive sampling strategy was employed, guided by four primary criteria to ensure relevance and data availability: (1) a stated objective linking tourism development with poverty alleviation; (2) the availability of audited sustainability or CSR reports containing quantifiable data on inputs and outputs; (3) a minimum operational history of two years to allow for outcome measurement; and (4) a clear focus on beneficiary communities identified as low-income (Wong et al., 2021). The required data were compiled from official corporate documents, including annual sustainability reports, dedicated CSR disclosures, and internal monitoring and evaluation records, which to some extent enhanced the objectivity of the input-output data.

Variable Selection and Justification. Following standard conventions for DEA (Cooper et al., 2007), three input and five output variables were selected. This selection process involved a review of the relevant literature and was further validated through consultation with a panel of experts, comprising three academic researchers and two practitioners with direct experience in CSR implementation in Indonesia. The chosen inputs reflect primary resource allocations: CSR Fund (IDR million, total financial investment), CSR Hours (person-hours, total human resource commitment), and Program Count (number, the diversity of activities undertaken within a program). The outputs aim to capture the multi-dimensional poverty alleviation and development goals of the programs: Local Participation (persons, count of direct beneficiaries engaged), Poverty Reduction (% reduction in the headcount poverty rate within the program's target area), Employment Created (jobs, number of direct and indirect jobs generated), Tourism Income (IDR million/year, estimated increase in local income attributable to tourism activities), and Infrastructure Index (1–5 scale, a composite score reflecting improvements in basic community infrastructure).

DEA Model Specification. Given that CSR programs typically work with relatively fixed budgets while aiming to maximize their social and economic outputs, an output-oriented BCC model under the assumption of Variable Returns to Scale (VRS) was deemed appropriate (Banker et al., 1984). The choice of VRS over Constant Returns to Scale (CRS) was statistically supported: a likelihood ratio test rejected the CRS assumption ($\chi^2 = 42.87$, $p < 0.001$), and the high coefficient of variation (>100%) across input variables confirmed significant heterogeneity in the operational scale of the sampled programs. Following Banker et al. (1984), each program was classified as exhibiting Increasing (IRS), Constant (CRS), or Decreasing (DRS) Returns to Scale based on the sum of its intensity variables ($\sum \lambda_j$). Scale efficiency was subsequently calculated as the ratio of the program's CRS efficiency score to its VRS efficiency score.

Stage 2: Structural Equation Modeling

Sample and Data Collection. The SEM phase of the research drew on survey data collected from 285 respondents. To ensure a comprehensive and balanced perspective on program impacts, the sample included three key stakeholder groups: direct beneficiaries (45.3%), local tourism entrepreneurs (28.4%), and program implementers or field officers (26.3%). This multi-stakeholder approach was intended to mitigate potential common method bias by incorporating varied viewpoints (Podsakoff

et al., 2003). The survey was administered in the field between March and May 2024, resulting in a response rate of 95%. Standard ethical protocols were followed, including obtaining informed consent from all participants and securing ethical approval from the authors' affiliated institution. Construct Operationalization and Measurement. All theoretical constructs were measured using reflective multi-item scales with a five-point Likert format (1 = strongly disagree to 5 = strongly agree). The items were adapted from established scales in the literature and refined for contextual relevance through a pre-test with 30 respondents (Hair et al., 2019). The constructs, along with their reliability coefficients (Cronbach's Alpha), are as follows: Exogenous Constructs – Data-Driven CSR Management (12 items, $\alpha=0.892$), Tourism Development Quality (9 items, $\alpha=0.865$), Community Empowerment (9 items, $\alpha=0.851$); Mediating Construct – SDG Implementation Effectiveness (9 items, $\alpha=0.901$); and Endogenous Construct – Poverty Alleviation Outcomes (9 items, $\alpha=0.879$).

PLS-SEM Estimation and Validation. The data were analyzed using SmartPLS 4.0 software, applying a path weighting scheme with 5,000 bootstrap subsamples for significance testing. PLS-SEM was selected over covariance-based SEM primarily due to its predictive orientation, its robustness in handling data that may not be normally distributed, and its suitability for complex models incorporating latent variables (Hair et al., 2019). The validity and reliability of the measurement model were assessed through standard criteria: indicator loadings (retained if >0.70), composite reliability (>0.80), average variance extracted (AVE >0.50), and discriminant validity (examined via the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio, with HTMT <0.85). Mediation effects were tested using the bootstrapping procedure outlined by Preacher and Hayes (2008), while potential moderating effects of the Returns to Scale (RTS) classification were examined through multi-group analysis (MGA).

Integration Protocol

To meaningfully combine the insights from both methodological stages, a specific integration protocol was followed. First, Unit of Analysis Alignment: the program-level efficiency scores generated by DEA were systematically matched with the aggregated, stakeholder-level construct scores from the SEM analysis using unique program identifiers. Second, Convergent Validity Check: Spearman's rank-order correlations were calculated to examine the relationship between the objective DEA efficiency scores and the perceptual constructs measured by SEM. Third, Causal Integration: the DEA efficiency score was incorporated as an independent variable in an Ordinary Least Squares (OLS) regression model, with the SEM-derived 'Poverty Alleviation Outcomes' construct as the dependent variable. Within this model, the mediating role of 'SDG Implementation Effectiveness' was formally tested, as suggested by Liu et al. (2013). The complete integrated analytical framework is presented in Figure 2.

RESULTS

DEA Results: Efficiency, Returns to Scale, and Benchmarks

Technical Efficiency Distribution. The average technical efficiency score is 78.34% (SD = 18.45%), suggesting the typical program can improve its outputs by approximately 27.7% using existing resources if it adopts practices observed among the best-performing programs (Cook & Seiford, 2009). The distribution is concentrated, with Nearly three-quarters of programs (72.4%) fall into either the Moderately Efficient (80–94%) or Moderately Inefficient (60–79%) categories, indicating

that most CSR programs operate within the intermediate efficiency range. This indicates that while most programs operate at moderate efficiency, substantial room for improvement remains across the portfolio.

Table 1. Distribution of BCC Technical Efficiency Scores

No	Efficiency Category	Range	Frequency	Percentage	Cumulative
1	Highly Efficient	≥95%	12	13.8%	13.8%
2	Moderately Efficient	80-94%	28	32.2%	46.0%
3	Moderately Inefficient	60-79%	35	40.2%	86.2%
4	Inefficient	<60%	12	13.8%	100.0%
Total			87	100.0%	

Returns to Scale Classification

Returns-to-scale analysis reveals notable variation: 43.7% of programs operate under Increasing Returns to Scale (IRS), 20.7% under Constant Returns to Scale (CRS), and 35.6% under Decreasing Returns to Scale (DRS), reflecting the diverse operational contexts of CSR programs in Indonesia.

IRS programs have the lowest mean efficiency (76.45%) and the smallest average budgets (IDR 12.8 billion), suggesting they could benefit from strategic scaling or increased resources. CRS programs, by contrast, show the highest average efficiency (84.12%) at moderate funding levels, consistent with an optimal operational scale for their program design.

DRS programs, despite receiving the highest average funding (IDR 45.2 billion), show relatively low efficiency (76.78%), pointing to possible coordination challenges or diseconomies of scale beyond a certain operational threshold (Banker et al., 1984). This disparity warrants particular attention, since large-scale CSR initiatives are common in Indonesia yet do not always translate into proportional impact.

Table 2. Returns to Scale Distribution and Characteristics

No	RTS Category	Frequency	%	Mean Efficiency	Mean CSR Fund	Interpretation
1	IRS	38	43.7%	76.45%	Rp 12.8M	Can benefit from scale-up
2	CRS	18	20.7%	84.12%	Rp 38.4M	Operating at optimal scale
3	DRS	31	35.6%	76.78%	Rp 45.2M	Experiencing diseconomies
Total		87	100.0%	78.34%	Rp 29.64M	

Scale Efficiency Analysis

On average, programs operate at 87.32% of their optimal scale potential, meaning roughly 12.68% of potential efficiency is lost to suboptimal operating scale. IRS programs show the lowest mean scale efficiency (84.23%), consistent with smaller-budget programs operating below optimal size and leaving scale economies untapped. DRS programs show moderate scale inefficiency (86.54%); while

not extreme, this combined with their characteristically high input intensity presents a managerial concern that merits attention.

Sectoral RTS Patterns and Strategic Implications

The distribution of returns to scale is not uniform across sectors (see Table 3). Banking is predominantly IRS (60%), likely reflecting the replicable, scalable nature of microfinance and community lending models, while energy and infrastructure show a clear dominance of DRS (50%), consistent with the complexity, longer timelines, and coordination challenges of large-scale physical projects. Telecommunications and manufacturing present a more balanced IRS/CRS/DRS mix, suggesting more mature or varied scaling strategies across program lifecycles (Lu et al., 2018). These sectoral variations suggest a one-size-fits-all scaling approach is unlikely to be effective.

Table 3. Returns to Scale by Organizational Type

No	Sector	IRS	CRS	DRS	Dominant RTS	Strategic Implication
1	Banking	60%	20%	20%	IRS	Scale-up microfinance
2	Energy & Infrastructure	25%	25%	50%	DRS	Restructure large projects
3	Telecommunications	42.8%	28.6%	28.6%	IRS	Expand digital programs
4	Manufacturing & FMCG	50%	16.7%	33.3%	IRS	Replicate successful models
5	Plantation & Agriculture	40%	30%	30%	IRS	Scale value-chain programs

Efficiency Frontier Programs and Critical Success Factors

An analysis of the top 15 programs forming the efficiency frontier (scores $\geq 93\%$) was conducted to identify characteristics contributing to their performance (detailed in Appendix A). Four factors recur among these programs. First, more diverse partnership networks: efficient programs engage significantly more institutional partners than less efficient ones (4.7 versus 2.1 partners, $t = 6.84$, $p < 0.001$), consistent with the view that collaborative networks enhance program reach and resource mobilization (Austin & Seitanidi, 2012). Second, holistic design: all frontier programs explicitly connect tourism activities with livelihood creation, infrastructure improvement, and environmental sustainability (Goodwin, 2016). Third, tangible community ownership: participatory design and management structures are universally present among frontier programs (Mikkilineni & Brown, 2020). Fourth, longer-term commitment: average operational duration is significantly greater than that of less efficient programs (6.2 versus 2.8 years, $t = 5.32$, $p < 0.001$), and 75% use structured monitoring and evaluation, indicating a data-informed management approach (Chen et al., 2018).

Slack Analysis for Inefficient Programs

For the 47 programs operating below 80% efficiency, a slack analysis was performed to pinpoint resource underutilization and output gaps as a roadmap for targeted improvement (see Table 4).

The most widespread shortfall is in poverty reduction output, with 87.2% of inefficient programs showing a deficit, indicating a common challenge in translating activities into measurable poverty impacts. More counterintuitively, slack in CSR financial allocation is present in 68.1% of programs, suggesting that inefficiency often stems not from resource scarcity but from suboptimal allocation or utilization (Cooper et al., 2007). Mean slack values and improvement potentials for each variable are summarized in Table 4.

Table 4. Slack Analysis for Inefficient Programs (n=47)

Variable	Mean Slack	% DMUs with Slack	Improvement Potential
INPUT SLACKS			
CSR Fund	IDR 12.4M	68.1%	23.4% reduction possible
CSR Hours	342 hours	55.3%	18.7% reduction possible
Program Count	1.8 units	46.8%	Focus vs. diversify trade-off
OUTPUT SLACKS			
Local Participation	487 persons	76.6%	89.2% increase needed
Poverty Reduction	2.34%	87.2%	65.8% increase needed
Employment Created	23.6 jobs	74.5%	94.3% increase needed
Tourism Income	IDR 178M	68.1%	102.7% increase needed
Infrastructure Index	0.87 points	63.8%	28.5% increase needed

On the input side, the most substantial slack is in CSR funding, with an average excess of IDR 12.4 million: 68.1% of inefficient DMUs can reduce expenditure by up to 23.4% while maintaining current output. Excess labor-hour utilization appears in over half of these programs, suggesting scope for streamlining operations, while slack in the 'program count' variable points to a trade-off between spreading resources across numerous activities and concentrating on a focused set of high-impact interventions.

On the output side, slack is more consequential developmentally: its high prevalence across local participation, poverty reduction, employment creation, and tourism income indicates that many programs struggle to convert inputs into tangible results. Employment creation and tourism income show the largest improvement potential, implying that jobs and local economic benefits require more deliberate, integrated program design rather than materializing automatically. Infrastructure gaps are comparatively modest, and their limited correlation with overall efficiency suggests that physical improvements alone are insufficient without integration into broader livelihood and market-access strategies.

SEM-PLS Results: Analysis of Causal Pathways

Measurement Model Evaluation

The measurement model shows satisfactory reliability and validity. All 48 indicator loadings meet the recommended threshold of 0.70, with most exceeding 0.80, and constructs demonstrate good internal consistency (Cronbach's alpha 0.851–0.901). Composite reliability (0.895–0.925) and average variance extracted (AVE 0.655–0.721) further support reliability and convergent validity (see

Table 5), while discriminant validity is confirmed through both the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratios, all below the 0.85 benchmark (Hair et al., 2019).

Table 5. Construct Reliability and Convergent Validity

Construct	Items	Cronbach's α	Composite Reliability	AVE	Assessment
Data-Driven CSR (DDC)	12	0.892	0.921	0.698	Excellent
Tourism Development Enhancement (TDE)	9	0.865	0.904	0.674	Very Good
Local Community Empowerment (LCE)	9	0.851	0.895	0.655	Good
SDG Implementation Effectiveness (SIE)	9	0.901	0.925	0.721	Excellent
Extreme Poverty Alleviation (EPA)	9	0.879	0.911	0.683	Very Good

Structural Model and Hypothesis Testing

Table 6. Structural Path Coefficients and Hypothesis Testing

Hypothesis	Path	β	t-value	p-value	f^2	Decision
H1	DDC $\rightarrow$ SIE	0.248	2.645	0.008**	0.078	Supported
H2	TDE $\rightarrow$ SIE	0.291	2.967	0.003**	0.104	Supported
H3	LCE $\rightarrow$ SIE	0.267	2.751	0.006**	0.089	Supported
H4	SIE $\rightarrow$ EPA	0.421	4.892	<0.001***	0.215	Strongly Supported
H5	DDC $\rightarrow$ EPA	0.182	2.145	0.032*	0.045	Supported
H6	TDE $\rightarrow$ EPA	0.195	2.256	0.024*	0.051	Supported
H7	LCE $\rightarrow$ EPA	0.174	2.045	0.041*	0.041	Supported

The structural model demonstrates satisfactory explanatory power, accounting for 59.2% of the variance in SDG implementation effectiveness and 67.4% of the variance in poverty alleviation outcomes. All seven proposed hypotheses receive empirical support, as summarized in Table 6. The effectiveness of SDG framework implementation shows the strongest direct relationship with poverty reduction ($\beta = 0.421$, $p < 0.001$), confirming the central mediating role of SDG alignment in translating program activities into tangible impacts and providing empirical weight to H4 and to the mediation analysis reported below (Scheyvens et al., 2016; Giménez Espín et al., 2026).

Mediation Analysis

The mediation analysis reveals that SDG implementation effectiveness plays a significant, partial mediating role, accounting for 36.4% of the total effect of data-driven CSR management, 38.5% of tourism development quality, and 39.2% of community empowerment on poverty reduction

outcomes. With all Variance Accounted For (VAF) values below 80%, this indicates complementary partial mediation (Preacher & Hayes, 2008), detailed in Table 7. This suggests that, within the Indonesian context, the SDGs function not as the sole pathway but rather as an important operational mechanism that works alongside other direct channels to convert program resources and activities into poverty reduction results.

Table 7. Specific Indirect Effects and Mediation Analysis

Mediation Path	Indirect Effect	t-value	p-value	VAF	Mediation Type
DDC → SIE → EPA	0.104	2.412	0.016*	36.4%	Partial
TDE → SIE → EPA	0.122	2.678	0.007**	38.5%	Partial
LCE → SIE → EPA	0.112	2.512	0.012*	39.2%	Partial

Predictive Relevance and Model Fit

The model's predictive relevance was assessed, with Q^2 values of 0.341 for SDG effectiveness and 0.412 for poverty reduction. Both values exceed the 0.25 threshold, which may indicate a medium-to-large level of predictive power (Hair et al., 2019). The standardized root mean square residual (SRMR) is 0.062, falling below the recommended 0.08 benchmark and suggesting an acceptable fit of the model to the data.

Integrated DEA-SEM Analysis

Convergent Validation

Table 8. Spearman Correlations – DEA Efficiency vs SEM Constructs (n=87)

SEM Construct	Correlation with BCC Efficiency (ρ)	p-value	Interpretation
Data-Driven CSR (DDC)	0.567***	<0.001	Strong positive
Tourism Development Enhancement (TDE)	0.612***	<0.001	Very strong positive
Local Community Empowerment (LCE)	0.489***	<0.001	Strong positive
SDG Implementation Effectiveness (SIE)	0.723***	<0.001	Very strong positive
Extreme Poverty Alleviation (EPA)	0.689***	<0.001	Very strong positive

To examine the coherence between the two methodological approaches, Spearman correlations were calculated between program-level DEA efficiency scores and the SEM's stakeholder-perception constructs. Results show strong positive correlations, particularly with SDG effectiveness ($\rho = 0.723$, $p < 0.001$) and poverty reduction outcomes ($\rho = 0.689$, $p < 0.001$), as presented in Table 8. This provides empirical support for the integrated approach and suggests that objectively measured

operational efficiency is meaningfully associated with stakeholders' perceptions of social impact (Liu et al., 2013).

Efficiency as a Predictor of Poverty Outcomes

An OLS regression using the DEA efficiency score to predict the SEM-derived poverty alleviation outcome score confirms a statistically significant positive relationship ($\beta = 0.087$, $t = 8.77$, $p < 0.001$), explaining 47.5% of the variance in poverty outcomes. A 10-percentage-point increase in CSR technical efficiency is equivalent to an estimated 0.087-point increase in the poverty alleviation score (measured on a 5-point Likert scale, maximum range = 4 points), underscoring the practical significance of efficiency improvements in enhancing poverty alleviation outcomes.

Moderation by Returns to Scale

The analysis further investigated whether the efficiency-outcome relationship varied by a program's returns-to-scale (RTS) classification. A multi-group analysis confirms a significant moderating effect (Chow test: $F = 3.87$, $p = 0.025$): the relationship is strongest under Increasing Returns to Scale (IRS, $\beta = 0.102$), moderate under Constant Returns to Scale (CRS, $\beta = 0.078$), and weakest under Decreasing Returns to Scale (DRS, $\beta = 0.071$). This result, detailed in Table 9, affirms that operational scale context meaningfully shapes how efficiency translates into impact (Banker et al., 1984).

Table 9. Multi-Group Regression by Returns to Scale Type

RTS Group	n	β_1 (Efficiency Coefficient)	R^2	Comparison
IRS	38	0.102*	0.521	IRS vs DRS: $\Delta\beta=0.031$, $p=0.018^*$
CRS	18	0.078***	0.468	CRS vs DRS: $\Delta\beta=0.007$, $p=0.621$
DRS	31	0.071***	0.412	IRS vs CRS: $\Delta\beta=0.024$, $p=0.042^*$

Efficiency Threshold Analysis

Examining outcomes across efficiency quartiles reveals a consistent positive relationship with no flattening effect. Programs in the lowest quartile (Q1, below 65%) achieve less than half the average poverty reduction of top-quartile programs (3.42% vs. 8.76%), and their cost-effectiveness is substantially worse – an estimated Rp 15.6 million per 1% poverty reduction, versus Rp 4.8 million for the most efficient programs, a 3.25-fold difference. The performance gap between Q1 and Q2 suggests that an efficiency level of approximately 65% may represent a pragmatic minimum threshold for viable impact in this context.

Mediation in the Integrated Model

In the final integrated model, examining the pathway from DEA efficiency to poverty reduction reveals balanced mediation: SDG effectiveness accounts for 51.7% of the total effect, with the remaining 48.3% a direct effect of efficiency on outcomes. This suggests two parallel, complementary pathways – an indirect route where operational efficiency enhances SDG

implementation quality, which then contributes to poverty reduction, and a more direct pathway where efficiency itself improves outcomes, possibly through cost savings, adaptive management, or stakeholder trust-building (Scheyvens et al., 2016).

DISCUSSION

This study's first contribution is diagnostic rather than purely methodological: combining DEA and PLS-SEM lets a CSR manager see not only which programs are efficient, but plausibly why. DEA alone would identify the 12 frontier programs without explaining what distinguishes them; PLS-SEM alone would test managerial pathways without an objective efficiency benchmark to validate them. The convergent correlations between DEA efficiency scores and SEM constructs, ranging from 0.489 to 0.723 and strongest for SDG Implementation Effectiveness ($\rho = 0.723$), indicate that the two measures capture related aspects of program performance rather than unrelated phenomena (Staessens et al., 2019). This supports a two-step diagnostic routine for CSR portfolios: use DEA scores to screen programs, then use SEM path coefficients — particularly on data-driven management and community empowerment — to identify which practices are most likely to move an underperforming program toward the frontier. This logic extends recent DEA applications to tourism-linked poverty alleviation, documenting substantial unexplained efficiency variation across space and time (Xiao et al., 2023; Zhang & Wu, 2024): the present findings suggest part of that variation is traceable to the managerial and stakeholder-engagement pathways captured by the SEM stage.

Second, efficiency and social mission are not in tension in this sample: more efficient programs are also associated with stronger poverty alleviation outcomes ($\beta = 0.087$, $p < 0.001$), and SDG Implementation Effectiveness mediates 51.7% of the efficiency-poverty relationship. This challenges the assumption that cost discipline crowds out social impact (Muthuri & Gilbert, 2011); instead, operationally poorly organized programs also deliver the weakest social returns. SDG alignment should therefore not be treated only as a reporting exercise. Because SDG Implementation Effectiveness carries the strongest direct path to poverty outcomes ($\beta = 0.421$) and channels roughly half of efficiency's total effect, it functions as an operational lever: CSR teams that build SDG indicators into internal monitoring and staff incentives, rather than only annual sustainability reports, are positioned to convert efficiency gains into measurable poverty reduction (Scheyvens et al., 2016). This mirrors evidence that SDG-oriented practices generate stronger organizational results as operational maturity increases from basic reporting toward advanced management integration (Giménez Espín et al., 2026), that firms translate external institutional pressure into internal CSR-SDG practice most effectively when embedded in day-to-day governance (Diab & Stubbs, 2025; Zenda et al., 2025), and that SDG-aligned CSR shapes employee pro-environmental behavior mainly through internal organizational climate rather than external communication (Kanwal et al., 2024).

Third, the strength of the efficiency-outcome link depends on a program's returns-to-scale (RTS) profile: strongest under Increasing Returns to Scale ($\beta = 0.102$) and weakest under Decreasing Returns to Scale ($\beta = 0.071$), even though DRS programs received the highest average funding. This cautions against uniform portfolio management: additional funding for large, DRS-classified programs is unlikely to yield proportional poverty-reduction returns, whereas comparable investment in smaller, IRS-classified programs appears more likely to pay off. This is consistent with a contingency view of CSR resource deployment (Donaldson, 2001) rather than a one-size-fits-all Resource-Based View reading (Barney, 1991). Section 'Managerial Implication' translates this scale-sensitive logic into a concrete portfolio classification for CSR managers and policymakers.

CONCLUSION

This study shows how an integrated quantitative approach can identify pathways for improving the social impact of CSR initiatives within existing resource constraints. Combining DEA and PLS-SEM moves the analysis beyond describing performance to exploring mechanisms through which operational efficiency is associated with poverty reduction in tourism-based CSR (Liu et al., 2013). Three insights arise from the Indonesian case.

First, the findings suggest a synergistic rather than antagonistic relationship between efficiency and social effectiveness: contrary to concerns that an efficiency focus undermines social missions, more efficient programs here are associated with greater poverty alleviation, underscoring the role of sound management in development-oriented CSR (Carroll & Shabana, 2010). Second, the SDGs function as more than aspirational targets – the significant mediating role of SDG implementation effectiveness shows that aligning CSR strategy with this framework provides a practical operational logic for channeling resources into measurable impact (Scheyvens et al., 2016). Third, a program's operational scale is a critical contingency: the varying strength of the efficiency-outcome relationship across IRS, CRS, and DRS classifications underscores the need for differentiated strategies on whether to scale, replicate, or restructure initiatives (Banker et al., 1984).

As pressure mounts to achieve the 2030 development agenda, evidence-based approaches for optimizing interventions become increasingly pertinent. The integrated framework here offers diagnostic and analytical tools – from efficiency benchmarking to causal-pathway testing – adaptable by researchers and practitioners in other contexts (Greswell & Plano Clark, 2017). Alleviating poverty ultimately requires not just resources and intent but a disciplined approach to learning from performance: for CSR managers, a practical starting point is a systematic efficiency review; for policymakers, integrating efficiency metrics into reporting and incentive structures can help steer resources toward more impactful uses.

MANAGERIAL IMPLICATION

For CSR managers and corporate leaders operating in Indonesia, the findings offer several practical considerations for portfolio management. Based on the analysis, a strategic classification of programs by both efficiency level and returns-to-scale (RTS) profile may be useful: programs with High Efficiency and IRS characteristics (such as certain scalable microfinance models) appear to be strong candidates for expansion and replication; High Efficiency CRS programs (like some established community-based ecotourism initiatives) might benefit most from efforts focused on standardization and systematic knowledge transfer; Low Efficiency IRS programs likely require internal operational improvements and capacity building before any significant scaling is considered; and for Low Efficiency DRS programs (which often include complex, large-scale infrastructure projects), a fundamental reassessment, restructuring, or even strategic exit may be warranted.

The analysis suggests that reallocating resources from the least efficient programs (bottom quartile) to those in the top quartile could, in theory, increase aggregate poverty reduction impact by approximately 42% without requiring new funding. In terms of investment priorities, the findings may indicate that focusing on data-driven management systems, deeper integration into local tourism value chains, and authentic community co-design processes could yield a higher return, as these factors influence outcomes through both direct and SDG-mediated pathways (Goodwin, 2016).

For Indonesian policymakers seeking to enhance the impact of private-sector social investment, several recommendations emerge from the findings. First, there may be merit in establishing incentives linked to program performance. Given the significant cost-effectiveness gap observed—where low-efficiency programs required over three times the resources per unit of poverty reduction compared to high-efficiency programs—consideration could be given to setting minimum efficiency thresholds for programs seeking tax deductions or public co-funding. Second, support mechanisms could be made more scale-sensitive. This might involve, for instance, offering matching grants to help promising small-scale (IRS) programs expand, providing technical assistance to replicate well-performing (CRS) models, and guiding the restructuring of large, complex (DRS) initiatives that show diminishing returns (Banker et al., 1984). Third, fostering deeper alignment with national and global development agendas could be encouraged through practical frameworks. Developing instruments like SDG-linked bonds, standardizing a core set of outcome metrics, and creating certification systems could help channel CSR activities more effectively toward the targets of the 2030 Agenda (United Nations, 2015).

LIMITATIONS AND FUTURE RESEARCH

This study is subject to several limitations. The cross-sectional data restrict causal claims about how efficiency evolves over time or long-term sustainability impacts; future research could employ panel DEA and longitudinal SEM designs to capture dynamic effects such as organizational learning (Wong et al., 2021). The exclusive focus on Indonesia may also limit generalizability to other institutional environments – comparative studies across other emerging economies would help test external validity (Hampton & Jeyacheya, 2020), particularly since evidence from the Lebanese tourism market shows the same broad poverty-alleviation drivers can combine quite differently elsewhere (El Zein et al., 2025), and a recent systematic review explicitly calls for more cross-country replication (Shah, 2025). Although multiple stakeholder groups were surveyed and respondent anonymity ensured, reliance on self-reported perceptual data in the SEM phase remains a limitation; future work should integrate these measures with objective administrative data such as household survey records or official poverty statistics (Podsakoff et al., 2003). Finally, the DEA model focuses primarily on economic and poverty-related outputs; a more comprehensive sustainability assessment would require environmental indicators and social-cohesion measures (Ashley et al., 2007), drawing on the community-empowerment and multi-stakeholder governance constructs increasingly used in Indonesian tourism-village research (Ferdian et al., 2024; Hendrayani et al., 2025; Wani et al., 2024).

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