Heritage and Sustainable Development
Vol. 8, No. 1, 2026, pp.209-224
https://doi.org/10.37868/hsd.v8i1.1793

(Online) ISSN 2712-0554
Original Research

Integrating tri-phase resilience and intangible benefits in project CBA: A tiered framework for critical infrastructure

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Received Dec. 9, 2025
Revised Feb. 18, 2026
Accepted Feb. 23, 2026
Online Mar. 4, 2026

Abstract

Critical-infrastructure project appraisal often undervalues resilience investments because many disruption impacts are non-market in origin yet material for stakeholders. This study proposes the tiered tri-phase resilience valuation framework plus (TRVF+), which integrates three operational resilience dimensions – preparedness, continuity maintenance, and restoration – into a CBA-compatible decision metric. TRVF+ computes normalized indices (PPI, CMI, SRI/SRI_adj) and a composite social stability index (CSSI); monetizes avoided disruption impacts (ADIC) from complaints, trust/satisfaction proxies, and regulatory standing; and propagates parameter uncertainty via Monte Carlo simulation (10,000 runs per case) to estimate a resilience-adjusted benefit–cost ratio (RABCR) and the decision-robustness probability Pr(RABCR>1.0). The framework is demonstrated on four anonymized pilot cases representing increasing data maturity (Tier 1–3). Monetized intangible benefits account for ~15–30% of total benefits on average (up to ~40% within Tier-1 uncertainty bounds). Across cases, baseline BCR values of 0.88–1.15 increase to post-intervention RABCR values of 1.10–1.45, and decision robustness meets or exceeds a moderate acceptance rule (Pr(RABCR>1.0)≥0.80; observed range 0.81–0.95). TRVF+ enables auditable valuation of resilience and supports communication of uncertainty in stakeholder consultations and public hearings.

Keywords: Resilience valuation, Cost–benefit analysis, Critical infrastructure, Intangible benefits, Preparedness, Continuity, Restoration, Monte Carlo simulation

1. Introduction

Cost–benefit analysis (CBA) remains a primary decision tool for infrastructure investments, but conventional appraisals often under-represent resilience because disruption costs extend beyond direct, market-priced losses. In critical infrastructure systems, cascading interdependencies can amplify service consequences and propagate impacts across sectors [1], [2]. While established CBA practice provides a structured basis for comparing investments, it typically treats many social and institutional effects only qualitatively [3], [4]. Resilience performance is commonly decomposed into preparedness, continuity maintenance during disruption, and speed of restoration. Beyond these operational dimensions, stakeholder trust, complaint dynamics, and regulatory standing can strongly shape perceived harm and post-event legitimacy, especially in stakeholder consultations and public hearings [5], [6]. These "intangible-origin" effects are often non-market in origin but can be proxied and monetized through avoided-cost and related valuation approaches [7], [8].

To address this valuation gap, this paper introduces the tiered tri-phase resilience valuation framework plus (TRVF+). TRVF+ operationalizes preparedness (PPI), continuity maintenance (CMI), and restoration speed (SRI, with criticality adjustment) as normalized indices, and captures stakeholder-facing impacts using a composite social stability index (CSSI) and avoided disruption impact cost (ADIC). These elements are integrated with conventional benefits and costs to compute a resilience-adjusted benefit–cost ratio (RABCR). Uncertainty is propagated via Monte Carlo sampling to estimate both expected RABCR and the probability that RABCR exceeds the decision threshold (Pr(RABCR>1.0)). A tiered implementation logic supports application under low, medium, and high data maturity.

1.1. Research gap & novelty

Resilience assessment has advanced from single-metric reliability notions to multi-dimensional, systems-oriented frameworks that explicitly consider interdependence, recovery trajectories, and adaptive capacity [9], [10]. Systematic reviews synthesize a wide range of measurement frameworks for critical infrastructure and highlight the need for consistent operationalization and comparability across contexts [11]. Related approaches quantify recovery performance and restoration speed, but typically stop short of providing a single CBA-compatible decision ratio that combines operational resilience and stakeholder-facing impacts [12], [13].

A second gap concerns valuation of non-market impacts. Recent work demonstrates that social response to infrastructure disruptions is context dependent and can change under compound stressors such as extreme temperature events [14]. Several studies provide monetization pathways for outage-related losses and broader societal impacts, yet these values are rarely integrated into project-level benefit–cost ratios in a way that preserves uncertainty and supports transparent acceptance criteria [15], [16]. Recent appraisal research further shows that communicating CBA outputs as probabilistic distributions (e.g., via Monte Carlo simulation) rather than single-point estimates materially improves decision transparency under uncertainty [17]. In parallel, organizational KPI-based approaches and project-management perspectives emphasize embedding resilience in routine processes, but commonly treat trust and legitimacy mechanisms as qualitative narratives rather than auditable inputs to appraisal [18], [19].

A third gap concerns implementation under heterogeneous data maturity. Sector-specific resilience metrics and optimization frameworks exist (e.g., for grid resilience), but organizations often lack guidance on how to translate available data into calibrated, probabilistic appraisal inputs that remain comparable across cases [20]. Some resilience engineering and cyber-resiliency frameworks provide structured capability taxonomies and risk-treatment logic, but do not prescribe how to translate such capabilities into a probabilistic, monetized decision metric for project appraisal [21], [22]. Operationally, this is particularly relevant for sectors where staffing, cross-training, and capacity-planning constraints shape the feasibility of resilience interventions [23]. In response, TRVF+ contributes: (I) an operationalization of tri-phase resilience (preparedness, continuity, restoration) as normalized indices suitable for cross-case comparison; (II) a structured pathway to monetize intangible-origin impacts (via CSSI and ADIC) and integrate them into a resilience-adjusted benefit–cost ratio; (III) explicit uncertainty propagation and a decision-robustness probability Pr(RABCR>1.0); and (IV) a tiered implementation logic that links data maturity and sectoral context to parameter calibration, weighting, and sensitivity analysis.

1.2. Research questions

This study addresses the following research questions:

(1) How can preparedness, continuity maintenance, and restoration speed be represented as normalized indices that are compatible with project appraisal?

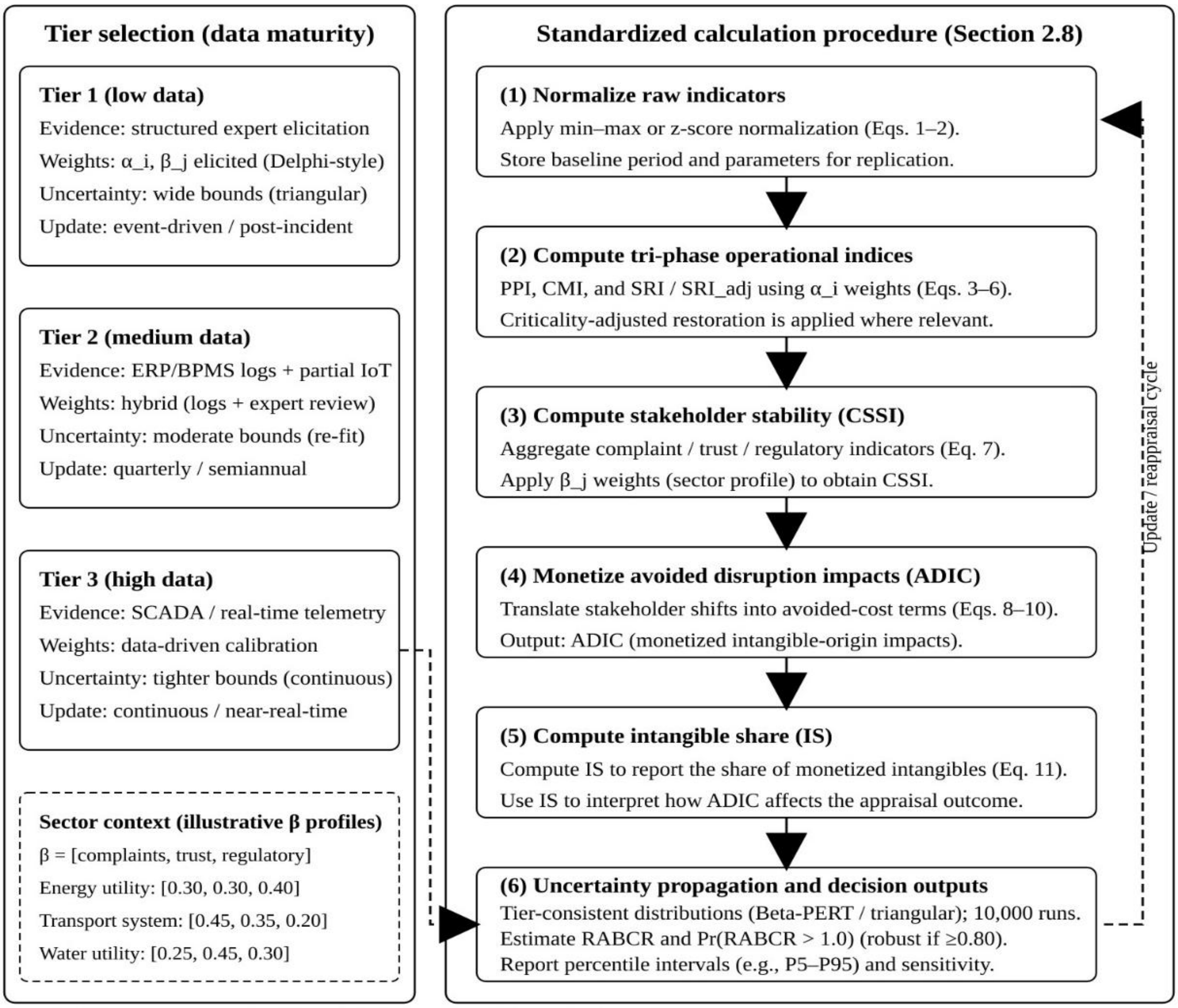
(2) How can intangible-origin disruption impacts be proxied, monetized, and integrated as avoided disruption impact costs within a benefit–cost ratio?

(3) How do data maturity and sectoral context affect parameter weighting, uncertainty bounds, and the decision robustness of resilience investments as measured by Pr(RABCR>1.0)?

1.3. Contribution and paper structure

This paper makes three contributions. First, it specifies TRVF+ as a CBA-compatible framework that integrates tri-phase resilience indices and monetized intangible-origin impacts into a resilience-adjusted benefit–cost ratio (RABCR) with an explicit decision-robustness probability Pr(RABCR>1.0). Second, it introduces a tiered implementation logic that supports adoption under low, medium, and high data maturity, providing practical guidance for parameter calibration, weight elicitation, and sensitivity analysis. Third, it demonstrates the approach on four anonymized pilot cases and reports cross-case patterns in both point estimates and uncertainty.

Figure 1 provides a practitioner-facing implementation roadmap: it separates tier-dependent choices (evidence sources, calibration of α_i and β_j, uncertainty bounds, and update cadence) from the tier-invariant computational core (normalization, index construction, ADIC monetization, and Monte Carlo-based robustness reporting). The roadmap also highlights where sectoral context can modulate stakeholder-weight profiles (β_j) and where accelerated reappraisal is warranted under rapid regulatory or political change. Figure 2 summarizes the integration logic of TRVF+. The remainder of the paper is structured as follows.



Legend: solid arrows = computational flow; dashed arrows = tier influence / update cycle.

Figure 1. Implementation roadmap showing tier-dependent (Tier 1–3) and standardized computational steps of TRVF+

Source: original figure developed by the authors

The remainder of the paper is structured as follows. Section 2 presents the research design, formal definitions, and calculation procedures. Section 3 reports results, cross-case comparisons, and positioning relative to prior work. Section 4 concludes with key findings and directions for further research.

2. Research method

This section describes the research design and the step-by-step calculation procedures used to apply TRVF+ across the four pilot cases, including data collection, parameter calibration, and uncertainty propagation.

2.1. Research design

This study uses a multiple-case study design with replication logic to develop and illustrate an appraisal framework in heterogeneous organizational settings [24], [25]. Four anonymized cases were selected to represent distinct critical-infrastructure contexts and increasing data maturity (Tier 1–3). The selection emphasized variation in the availability and quality of operational logs, customer-feedback proxies, and telemetry, enabling assessment of how TRVF+ can be implemented under different information constraints.

The empirical material combines (I) organizational operational records (e.g., service downtime logs, restoration timestamps, work-order histories), (II) aggregated customer-feedback indicators (e.g., complaint counts and trust/satisfaction proxies), and (III) where available, telemetry and regulatory performance signals. This mixed evidence base supports both structured expert elicitation (Tier 1) and data-driven calibration (Tier 2–3), consistent with pragmatic mixed-method approaches in applied infrastructure research [26]. The aim is decision-support and valuation transparency; the study does not claim causal identification of intervention effects.

2.2. TRVF+ framework

TRVF+ integrates operational resilience performance and stakeholder-facing impacts into a single appraisal structure (Figure 2). The framework combines three operational indices—Proactive Preparedness Index (PPI), Continuity Maintenance Index (CMI), and Speed of Restoration Index (SRI, with a criticality-adjusted variant SRI_adj)—with a Composite Social Stability Index (CSSI) and monetized avoided disruption impact costs (ADIC). Operational indices are constructed from normalized input metrics and are bounded on [0,1] to facilitate comparability across cases.

The valuation logic proceeds as follows. First, operational indices (PPI, CMI, SRI/SRI_adj) summarize the expected effect of resilience interventions on preparedness, continuity during disruption, and restoration speed. Second, CSSI captures the stakeholder-facing response using aggregated, anonymized indicators (complaints, trust/satisfaction, and regulatory standing). Third, these elements are translated into an avoided disruption impact cost (ADIC), which is then integrated with conventional benefit and cost terms to compute a resilience-adjusted benefit–cost ratio (RABCR). Finally, uncertainty in inputs and parameters is propagated using Monte Carlo simulation, yielding both expected RABCR and the decision-robustness probability Pr(RABCR>1.0).

Figure 2 summarizes the TRVF+ integration logic as a tiered but computationally consistent appraisal workflow. The tiered implementation (Tier 1–3) specifies the evidence base, the calibration approach for weights (αi for PPI components and βj for CSSI components), and the width and update frequency of uncertainty bounds, while preserving a common computational core. Operational evidence is mapped to three normalized tri-phase indices - preparedness (PPI), continuity maintenance (CMI), and restoration speed (SRI, with a criticality-adjusted variant SRI_adj where relevant). In parallel, aggregated stakeholder indicators (complaint density, trust/satisfaction proxies, and regulatory standing) are combined into CSSI. Changes in stakeholder stability are monetized as avoided disruption impact costs (ADIC), capturing “intangible-origin” effects that are not represented in conventional CBA. Finally, conventional CBA terms, operational resilience effects, and ADIC are integrated into the resilience-adjusted benefit–cost ratio (RABCR). Parameter uncertainty is propagated via Monte Carlo simulation, enabling the study to report both expected RABCR and the robustness metric Pr(RABCR>1.0).

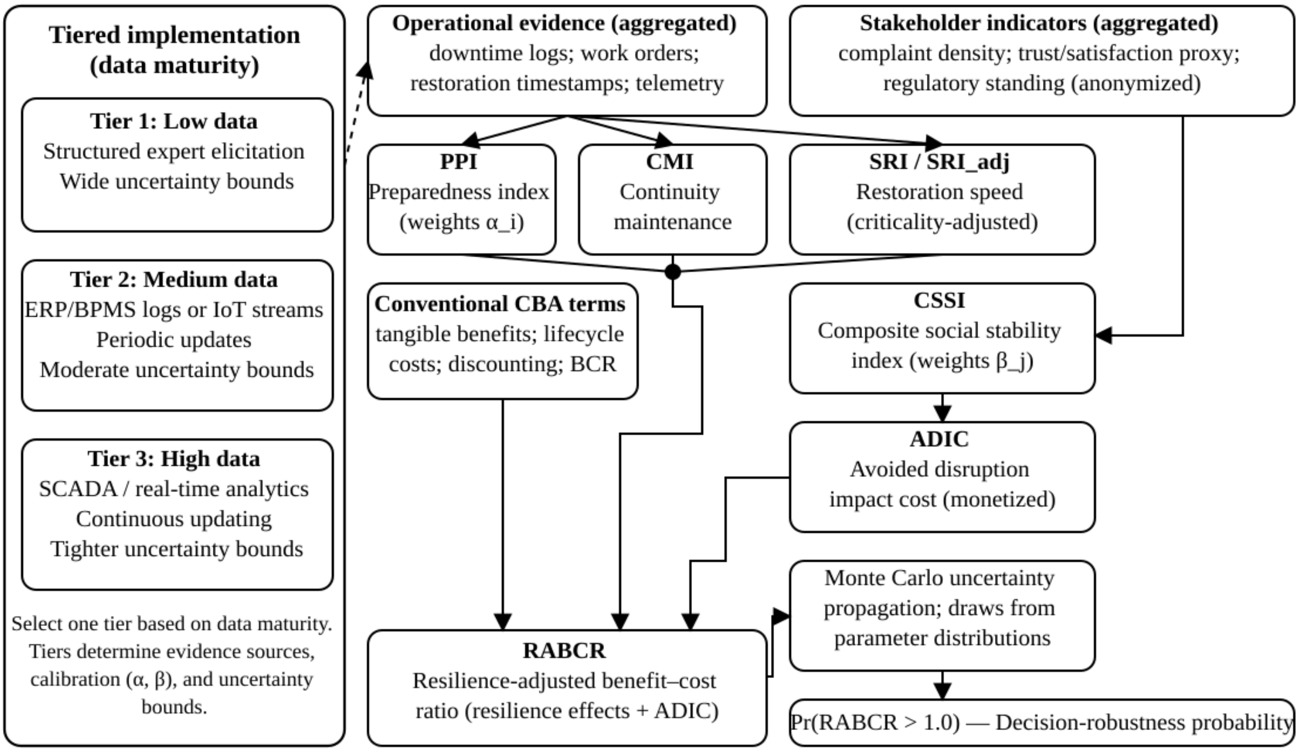


Figure 2. TRVF+ integration logic and information flow across tiered implementation, operational indices, stakeholder indicators, and decision robustness metrics

Source: original figure developed by the authors

2.3. Normalization procedure

To ensure comparability across cases and indicators, TRVF+ normalizes heterogeneous metrics onto a common scale. For bounded metrics with known minimum and maximum values, min–max scaling is applied as in (1) so that normalized values lie in [0,1]. For unbounded metrics or metrics without stable bounds, z-score standardization is applied as in (2) to express deviations relative to the observed mean and standard deviation [27], [28].

$$\phi(x) = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

$$z(x) = \frac{x - \bar{x}}{\sigma} \tag{2}$$

The normalization approach is selected per indicator based on measurability and interpretability. For example, ratios such as Backup Assets/Critical Assets and shares such as CrossTraining naturally admit bounded scaling, while metrics such as absolute restoration time may be standardized if bounds are not stable across contexts. All normalization choices and parameter values (min, max, mean, standard deviation) are recorded in the case parameter sheets to support replicability.

2.4. Tri-phase resilience indices

TRVF+ represents tri-phase resilience using three bounded indices: preparedness (PPI), continuity maintenance (CMI), and restoration speed (SRI). PPI in (3) is computed as a weighted sum of four normalized preparedness components: (I) Backup Assets/Critical Assets (ratio of available backup units or capacity to identified critical assets), (II) CrossTraining (share of staff cross-trained for emergency roles), (III) Drill Frequency (frequency of full-scale response exercises per year, normalized to a reference period), and (IV) Plan Robustness (a structured score of emergency-plan completeness and testability based on documented checklist criteria). The weights αi (i=1,…,4) are non-negative and sum to 1.

$$PPI = \alpha_1 \, \phi\left(\frac{Backup\ Assets}{Critical\ Assets}\right) + \alpha_2 \, \phi(CrossTraining) + \alpha_3 \, \phi(Drill\ Frequency) + \alpha_4 \, \phi(Plan\ Robustness) \tag{3}$$

CMI in (4) captures the ability to maintain baseline service during disruption. It compares expected service delivery under disruption to a baseline service level (BaseService) and is bounded on [0,1]. When Baseline Service is near zero, CMI is set to 0 by convention to avoid division artifacts and to reflect the lack of meaningful continuity.

$$CMI = 1 - \frac{Peak\ Degradation}{Baseline\ Service} \tag{4}$$

SRI in (5) captures restoration speed by comparing observed or expected restoration time (RestoreTime) to an allowable outage or target recovery window (AllowableOutage). Because restoration priorities differ by asset criticality, SRI_adj in (6) incorporates a criticality weight w_crit∈[0,1], derived from the case-specific criticality register and continuity priorities [29], [30].

$$SRI = \max\left(0{,}1 - \frac{Mean\ Time{-}to{-}Recover}{Max\ Allowable\ Outage}\right) \tag{5}$$

$$SRI_{adj} = SRI + w_{crit} \cdot \phi(Node\ Criticality) \tag{6}$$

2.5. Intangible valuation, CSSI, and ADIC

In TRVF+, the term “intangible” refers to disruption impacts that are non-market in origin (e.g., trust erosion, reputational damage, institutional friction) but that can be monetized through proxy valuation methods. Once monetized, these values are treated consistently with CBA: they are incorporated into the appraisal via avoided disruption impact costs (ADIC).

Stakeholder-facing impacts are summarized using the Composite Social Stability Index (CSSI) in (7), which combines normalized indicators of complaint dynamics (ComplaintDensity), a trust/satisfaction proxy (TrustScore), and regulatory standing (RegulatoryStanding). The weights βj (j=1,…,3) are non-negative and sum to 1. Weights reflect sectoral salience: for example, regulated utilities may place greater weight on regulatory standing, while customer-facing service contexts may emphasize complaint dynamics [31], [32].

$$CSSI = \beta_1 \phi\left(\frac{Complaints}{Population}\right) + \beta_2 \phi(Trust\ Score) + \beta_3 \phi(Regulatory\ Standing) \tag{7}$$

ADIC in (8) monetizes the avoided disruption impacts implied by improvements in CSSI and related quantities. Following avoided-cost logic, expected loss E[L] is decomposed into tangible and intangible components as in (9), and the intangible component is monetized using unit-cost parameters (e.g., cost per complaint handling, monetized trust/satisfaction shifts, and monetized regulatory performance shifts) as formalized in (10) [4], [15].

$$ADIC = E[L_{no-res}] - E[L_{with-res}] \tag{8}$$

$$E[L] = \textstyle\sum_i p_i(T_i + I_i) \tag{9}$$

$$I_i = \Delta(Complaints) \times CostPerComplaint + \Delta(Trust\ Score) \times ReputationCost + \cdots \tag{10}$$

Unit monetization parameters are calibrated in a tier-consistent manner. In Tier 1, parameters are elicited from structured expert judgement and triangulated with internal accounting proxies (e.g., burdened labor cost per complaint handling episode, documented customer-retention costs, or historical penalty/compensation practices). In Tier 2–3, parameters can be refined using incident records and observed relationships between disruption characteristics and stakeholder indicators [16]. The intangible share (IS) in (11) reports the proportion of total monetized benefits that originates from ADIC, supporting transparent interpretation of the role of non-market impacts.

$$IS = \frac{ADIC}{Tangible\ Benefits + ADIC} \tag{11}$$

2.6. Decision ratio and uncertainty propagation

The resilience-adjusted benefit–cost ratio (RABCR) in (12) integrates conventional CBA terms with monetized resilience and avoided disruption impacts (including ADIC). To account for uncertainty in costs, benefits, and valuation parameters, TRVF+ propagates uncertainty through Monte Carlo sampling. Cost and duration inputs are parameterized using Beta-PERT distributions when expert estimates include optimistic, most-likely, and pessimistic values [33]. Triangular distributions are used where only bounded ranges and a most-likely value are available, particularly for monetization parameters in low-data settings.

$$RABCR = \frac{Tangible\ Benefits + ADIC}{Lifecycle\ Cost} \tag{12}$$

Decision robustness is defined as the probability that RABCR exceeds the acceptability threshold of 1.0, i.e., Pr(RABCR>1.0). In this study, a project is considered decision robust when Pr(RABCR>1.0)≥0.80, reflecting a moderate risk tolerance that balances confidence with practical feasibility. This threshold is a study choice rather than a fixed standard; consistent with ISO 31000, acceptance criteria should be calibrated to organizational context and stakeholder expectations [34].

When dependencies between inputs are material (e.g., between outage duration and complaint volume), correlations are explicitly modeled in the Monte Carlo sampling to avoid overstating diversification benefits [35].

2.7. Tiered implementation

TRVF+ is designed for tiered implementation based on data maturity.

Tier 1 (low data) relies primarily on structured expert elicitation to estimate baseline metrics, intervention effects, and plausible uncertainty bounds. Expert judgement is elicited using a Delphi-style process, reporting medians and bounded ranges for key parameters, and documenting convergence and disagreement metrics (e.g., interquartile ranges) to support transparency [9].

For Tier 1 implementations, elicited weight vectors are normalized to satisfy Σα_i = 1 and Σβ_j = 1, and the dispersion of expert judgements is reported alongside the medians (e.g., via interquartile ranges). This documentation provides an explicit audit trail for why subsequent sensitivity ranges are applied and which indicators dominate the valuation under low-data uncertainty.

Tier 2 (medium data) complements expert judgement with partial operational logs (e.g., ERP/BPMS work orders and downtime records) and periodic stakeholder indicators. Parameters and weights can be updated at regular intervals (e.g., quarterly) as new incident data become available, enabling gradual tightening of uncertainty bounds and calibration of the relationship between operational performance and stakeholder-facing indicators [36], [37].

Tier 3 (high data) leverages real-time telemetry (e.g., SCADA, IoT sensor feeds) and continuous monitoring to support near-real-time parameter updating. Bayesian updating and related probabilistic methods can incorporate new evidence to revise beliefs about disruption frequencies, restoration performance, and stakeholder responses, improving predictive precision as data accumulate [38]. Digital-twin or near-real-time analytics architectures can further support this continuous calibration where available [39].

Across tiers, sectoral context shapes the weighting and calibration strategy for stakeholder-facing indicators (β_j in CSSI) as well as the associated unit monetization parameters used in ADIC. For example, in energy utilities, disruptions are immediately perceptible and often safety-critical; rapid public backlash and compliance exposure can increase the relative salience of complaint density, trust proxies, and regulatory standing. In transport systems, the availability of alternative routes or modes may moderate some impacts, while political sensitivity to service quality can make complaint dynamics particularly influential during major disruptions. Accordingly, TRVF+ users should document sector-specific weight profiles and test them through sensitivity analysis (e.g., ±10–20% relative shifts in β_j) to assess whether the decision-robustness conclusion remains stable under plausible alternative assumptions. Figure 1 makes this sectoral modulation explicit by providing illustrative starting profiles for β_j (complaints, trust, regulatory), which can then be adapted to the organizational context and stress-tested through sensitivity analysis.

2.8. Data collection and analysis

Data collection focused on operational performance metrics, stakeholder-facing indicators, and monetization proxies. Operational metrics were extracted from organizational records (e.g., downtime logs, restoration timestamps, work orders) and, where available, telemetry streams. Stakeholder-facing indicators were aggregated and anonymized (e.g., complaint counts per period, normalized trust/satisfaction proxies, regulatory performance scores) to avoid processing personally identifiable information.

The end-to-end workflow is visualized in Figure 1; the numbered procedure below implements the same sequence to support replication across cases and tiers.

Analysis followed a standardized calculation procedure:

(1) Normalize each raw indicator using (1) or (2) as appropriate.
(2) Compute PPI, CMI, and SRI/SRI_adj using (3)–(6).
(3) Compute CSSI using (7).
(4) Monetize avoided disruption impacts and compute ADIC using (8)–(10).
(5) Compute the intangible share IS using (11).
(6) Parameterize uncertain inputs (costs, durations, unit monetization parameters) with tier-consistent distributions and run Monte Carlo simulation (10,000 iterations per case) to estimate RABCR and Pr(RABCR>1.0).

To support reproducibility, each case implementation maintains a parameter log that records: (I) raw indicator definitions, data sources, and any preprocessing steps; (II) normalization choices and the associated parameter values (e.g., min–max bounds, baseline periods, or z-score statistics); (III) the complete α_i and β_j weight vectors and their elicitation or estimation method (e.g., Delphi rounds, data-driven calibration, or hybrid approaches); (IV) unit monetization parameters used in ADIC, including the assumed valuation basis and any currency conversion or deflation/inflation adjustments; (V) distributional assumptions for uncertain inputs (distribution type, parameter values, and truncation rules if applied); (VI) correlation assumptions used in Monte Carlo sampling (including the structure and coefficients); and (VII) simulation settings (number of iterations and the random seed). Reporting these items enables independent replication of RABCR and Pr(RABCR>1.0) under the stated assumptions.

When historical episodes were available, a basic validation step was performed through back-testing: incident-specific predictions (e.g., expected complaint volume, restoration duration, and implied ADIC) were compared against observed logged values to assess plausibility and parameter stability. As expected, lower-data tiers exhibited wider error bands (approximately 10–25%), while higher-data tiers achieved tighter agreement under stable operating conditions [40].

2.9. Ethical considerations

All participating organizations provided access to anonymized operational records and aggregated customer-feedback indicators without personally identifiable information. Expert participants in structured elicitation (Tier 1 Delphi panels) were organizational personnel who contributed in their professional capacity. Oral informed consent was obtained regarding the use of anonymized judgements for research purposes. Aggregate findings were reviewed by each organization prior to manuscript finalization to ensure anonymity. Since no personally identifiable data were collected or processed and expert participation occurred within professional scope, formal institutional ethics review was not required under the organizations' internal policies. The study followed principles of confidentiality and data minimization throughout.

3. Results and discussion

This section reports results from the four pilot applications of TRVF+ and interprets cross-case patterns. Results are reported in terms of pre/post index values (PPI, CMI, SRI/SRI_adj, CSSI), monetized avoided disruption impacts (ADIC) reported per case, the resilience-adjusted benefit–cost ratio (RABCR), and the associated decision-robustness probability Pr(RABCR>1.0). Table 1 provides the consolidated cross-case summary of index changes, intangible shares, and decision outputs.

3.1. TRVF+ implementation results

Across the four pilot cases, TRVF+ translates operational resilience improvements and stakeholder-facing impacts into CBA-compatible decision outputs. Table 1 summarizes pre/post values for the tri-phase operational indices, CSSI, ADIC, and the resulting decision metrics. Baseline (conventional) BCR values range from 0.88 to 1.15; after incorporating resilience effects and monetized intangible-origin impacts, post-intervention RABCR values range from 1.10 to 1.45. Decision robustness meets or exceeds the moderate acceptance rule in all cases (Pr(RABCR>1.0) ranges from 0.81 to 0.95).

Monetized intangible benefits constitute a material share of total benefits. Across cases, the intangible share ranges from 15% to 30% on average, and Tier 1 exhibits wider uncertainty bounds due to broader parameter ranges and greater reliance on expert judgement. These results motivate reporting both expected RABCR and Pr(RABCR>1.0) to communicate uncertainty transparently.

3.2. Individual case findings

3.2.1. Case A (Tier 2)

Case A (Tier 2) demonstrates a medium-data implementation combining operational logs with aggregated stakeholder indicators. Preparedness improved from PPI 0.62 to 0.70, reflecting increased backup capacity, expanded cross-training, and more formalized emergency planning. Continuity and restoration improvements were more modest (CMI 0.85→0.86; SRI 0.75→0.78), while stakeholder-facing performance improved from CSSI 0.66 to 0.75. The implied avoided disruption impact cost is ADIC 160 kLCU, corresponding to an intangible share of 25% of total monetized benefits. The baseline BCR of 0.95 increases to a post-intervention RABCR of 1.20, with decision robustness Pr(RABCR>1.0)=0.87.

3.2.2. Case B (Tier 1)

Case B (Tier 1) represents a low-data setting where structured expert elicitation and bounded uncertainty ranges are central to parameterization. Preparedness increased from PPI 0.44 to 0.55, while continuity and restoration indices changed modestly (CMI 0.68→0.70; SRI 0.60→0.62). Stakeholder-facing performance improved from CSSI 0.58 to 0.64. The implied avoided disruption impact cost is ADIC 140 kLCU, with an average intangible share of 30% (±10% within the Tier-1 uncertainty bounds). Although the conventional baseline BCR is 0.88, incorporating resilience and monetized intangible benefits yields RABCR 1.10. Due to wider parameter uncertainty, the robustness probability is lower than in other cases but still meets the acceptance rule: Pr(RABCR>1.0)=0.81.

3.2.3. Case C (Tier 2)

Case C (Tier 2) combines operational records with systematic incident logging, enabling tighter calibration of restoration performance. Preparedness improved from PPI 0.64 to 0.72 and continuity remained high (CMI 0.88→0.90). Restoration improved materially when accounting for criticality (SRI/SRI_adj 0.75→0.82), and stakeholder-facing performance improved from CSSI 0.72 to 0.80. The avoided disruption impact cost is ADIC 120 kLCU, corresponding to an intangible share of 15%. The baseline BCR is approximately neutral (1.00), while the post-intervention RABCR rises to 1.22 with Pr(RABCR>1.0)=0.90.

3.2.4. Case D (Tier 3)

Case D (Tier 3) illustrates a high-data implementation leveraging near-real-time telemetry and structured performance monitoring. Preparedness and continuity were already high and improved modestly (PPI 0.81→0.85; CMI 0.92→0.92), while criticality-adjusted restoration performance improved from SRI_adj 0.78 to 0.85. Stakeholder-facing indicators remained strong (CSSI 0.86→0.88). The implied avoided disruption impact cost is ADIC 180 kLCU, representing an intangible share of 20%. The conventional baseline BCR is 1.15; TRVF+ yields RABCR 1.45 with a high robustness probability Pr(RABCR>1.0)=0.95, consistent with tighter uncertainty bounds under higher data maturity.

3.3. Cross-case comparison

Table 1 provides a consolidated cross-case summary of pre/post indices, intangible shares, and decision outputs. Three cross-case patterns are notable.

First, preparedness improvements (PPI) are the most consistently observed across cases, reflecting the relative tractability of interventions such as backup capacity, cross-training, drills, and formal planning. Continuity (CMI) and restoration (SRI/SRI_adj) improvements are more heterogeneous, consistent with greater dependence on external constraints (e.g., supply chains, field conditions, and interdependent infrastructure).

Second, monetized intangible-origin impacts are material in every case. The average intangible share ranges from 15% to 30%, and the widest uncertainty bounds occur in Tier 1, where unit monetization parameters and weights rely more heavily on expert judgement. This supports reporting both the expected ratio (RABCR) and the robustness probability Pr(RABCR>1.0) rather than relying on a single point estimate.

Interpretation of variability. Variability in Monte Carlo outputs arises from (I) uncertainty in operational improvements (pre/post index shifts), (II) uncertainty in unit monetization parameters used to compute ADIC, and (III) context-dependent stakeholder responses that can change across events. Tiered implementation helps interpret this dispersion: Tier 1 typically exhibits wider posterior ranges, while Tier 2–3 enable tighter calibration and narrower uncertainty bands as data quality and frequency improve. In reporting, dispersion can be summarized using the median and percentile intervals (e.g., P5–P95), while Pr(RABCR>1.0) provides a single decision-relevant measure of whether uncertainty materially threatens the investment case.

Table 1. Cross-case summary: pre/post index values, intangible share, baseline BCR, post-intervention RABCR, and decision robustness (Pr(RABCR>1.0))

Company & Tier	**PPI (Baseline → Post)**	**CMI (Baseline → Post)**	**SRI / SRI_adj (Baseline → Post)**	**CSSI (Baseline → Post)**	**Intangible Share (%)**	**Final RABCR (Prob>1.0)**	**Baseline BCR**
A (Tier 2)	0.62 → 0.70	0.85 → 0.86	0.75 → 0.78	0.66 → 0.75	~25	1.20 (87%)	~0.95
B (Tier 1)	0.44 → 0.55	0.68 → 0.70	0.60 → 0.62	0.58 → 0.64	~30 (±10)	1.10 (81%)	~0.88
C (Tier 2)	0.64 → 0.72	0.88 → 0.90	0.75 → 0.82	0.72 → 0.80	~15	~1.22 (90%)	~1.00
D (Tier 3)	0.81 → 0.85	0.92 → 0.92	0.78 → 0.85 (adj.)	0.86 → 0.88	~20	~1.45 (95%)	~1.15

Source: authors' own elaboration based on case study data

3.4. Unexpected observations

Two observations emerged across the pilot applications. First, improvements in preparedness (PPI) did not always translate proportionally into continuity (CMI) or restoration (SRI/SRI_adj) gains, highlighting that operational resilience is constrained by dependencies outside an organization's immediate control. Second, higher-frequency and higher-quality monitoring (Tier 3) enabled tighter uncertainty bounds and more stable parameter calibration, improving the interpretability of RABCR and Pr(RABCR>1.0) over time. This aligns with the general expectation that richer sensor and monitoring infrastructures support more reliable resilience analytics, provided that data quality and representativeness are managed explicitly [41].

3.5. Connecting to the literature

This section positions TRVF+ relative to alternative decision-support approaches used in infrastructure resilience appraisal. Conventional CBA focuses on monetized market impacts and typically reports a baseline benefit–cost ratio (BCR) without an explicit representation of stakeholder-facing impacts and parameter uncertainty beyond scenario analysis [3]. TRVF+ extends this logic by integrating tri-phase operational indices and monetized intangible-origin impacts into a resilience-adjusted ratio (RABCR) and by reporting a probabilistic robustness metric Pr(RABCR>1.0).

Compared with purely engineering-focused reliability or resilience indices, which quantify service availability and recovery performance (often via interruption frequency and duration metrics) but are frequently disconnected from investment appraisal, and with macroeconomic impact assessments that estimate aggregate losses at the economy or sector level without indicating which project-level interventions to prioritize, TRVF+ provides an auditable bridge between operational performance and monetized decision outputs. While MCDA frameworks can incorporate multiple non-market criteria and support deliberation, they often yield composite scores or ordinal rankings rather than a CBA-compatible acceptance rule. By monetizing intangible-origin impacts through ADIC and integrating them with conventional CBA terms into RABCR, TRVF+ supports transparent portfolio selection while still allowing stakeholder-facing dynamics and uncertainty to be reported explicitly via Pr(RABCR>1.0) rather than relying on point estimates alone.

Multi-criteria decision analysis (MCDA) approaches can incorporate non-market criteria directly and support stakeholder deliberation, but they often produce ordinal rankings or composite scores rather than a CBA-compatible ratio that can be compared to budget constraints and standard investment rules [42]. Optimization and recovery scheduling models can produce operationally efficient plans, yet may not directly translate operational gains into a transparent monetized appraisal suitable for cross-project portfolio selection [30]. Resilience stress-testing approaches provide uncertainty-aware evaluation of critical infrastructure under extreme scenarios and can complement the probabilistic decision logic used in TRVF+ [43].

Finally, dynamic planning and resilience governance approaches emphasize interdependence, adaptive capacity, and compound hazards [8], [44]. Sector-specific quantitative metrics have also been proposed, particularly in energy and transport, but these often remain index-based rather than directly integrated into monetized project appraisal [20], [45]. TRVF+ complements these perspectives by providing an auditable valuation layer that can be used alongside engineering specifications and governance processes to communicate the expected value and robustness of resilience investments.

3.6. Theoretical contributions

TRVF+ contributes theoretically by linking resilience capability constructs to monetized decision outputs under uncertainty. First, it formalizes a tractable mapping from tri-phase operational resilience (preparedness, continuity, restoration) and stakeholder-facing dynamics (complaints, trust proxies, regulatory standing) into a unified appraisal metric (RABCR) with a probabilistic robustness interpretation. This advances work that treats resilience as a multi-dimensional property by providing an explicit economic decision lens.

Second, the tiered implementation logic supports contingency-oriented reasoning: as data maturity increases, the framework shifts from expert-elicited priors to evidence-based calibration and updating, enabling adaptive refinement of valuation parameters and uncertainty bounds [46], [47]. This aligns with decision-making perspectives that emphasize context, learning, and iterative adjustment in complex infrastructure systems.

Third, by reporting Pr(RABCR>1.0) alongside expected RABCR, TRVF+ contributes to the literature on resilience decision-making under uncertainty by operationalizing a transparent acceptance criterion that can be audited and debated in stakeholder settings [48].

3.7. Practical implications

TRVF+ has several practical implications for infrastructure owners and public decision makers:

(1) Adopt a tiered implementation strategy. In low-data settings, begin with structured expert elicitation and bounded ranges; in medium- and high-data settings, progressively tighten uncertainty bounds using operational logs and telemetry.

(2) Report both expected RABCR and decision robustness Pr(RABCR>1.0) to support transparent, uncertainty-aware investment decisions and to reduce overreliance on point estimates.

(3) Use RABCR and Pr(RABCR>1.0) as communication tools in stakeholder consultations and public hearings. Presenting both the mean ratio and the robustness probability helps explain why certain resilience investments remain justified under uncertainty, including when social and political considerations prevail over purely technical arguments [6].

(4) Document sectoral weighting choices (e.g., relative emphasis on complaints, trust proxies, and regulatory standing) and test them through sensitivity analysis to ensure that conclusions are stable under plausible alternative profiles, consistent with resilient-infrastructure decision principles [22].

3.8. Limitations

This study has several limitations. First, in low-data environments, unit monetization parameters and weight vectors rely on expert judgement and accounting proxies, which increases uncertainty and may introduce bias. Second, the framework is designed for decision support rather than causal inference; observed pre/post differences should be interpreted as appraisal inputs under stated assumptions.

Third, model accuracy may decline in contexts of rapid structural change - such as political instability, abrupt regulatory regime shifts, or rapid changes in stakeholder behavior - because key parameters (e.g., complaint response, trust dynamics, enforcement intensity) may drift across contexts and events. This limitation is aligned with broader systemic-risk governance concerns [49], [50]. Evidence also indicates that societal impacts of infrastructure disruptions depend on behavioral responses that can change across contexts and events [51]. In such contexts, scenario-based bounds and shorter reappraisal cycles are recommended, and conclusions should be interpreted as conditional on the stated regulatory and political assumptions.

For operational guidance, a shortened reappraisal cycle of 1–3 months is recommended when major structural shifts occur (e.g., tariff restructuring, new compliance mandates, or political transitions that materially change enforcement intensity). During such periods, widening the uncertainty bounds on CSSI-related parameters provides a conservative adjustment until conditions stabilize, consistent with the update logic highlighted in Figure 1. Finally, the pilot cases cover a limited set of sectors and hazards. Compound and cascading disruptions in interdependent infrastructure systems may require richer dependency modeling and more frequent parameter updating than implemented here [8].

3.9. Further research

Further research should (I) test TRVF+ on a wider portfolio of sectors and disruption types, including compound hazard scenarios; (II) develop sector-specific default calibration profiles and public benchmarks for unit monetization parameters; and (III) extend Tier 3 implementations with formal online updating and digital-twin integration where feasible. Additional work on longitudinal validation would clarify the stability of stakeholder-facing proxies and the conditions under which uncertainty bounds can be tightened without overstating confidence.

4. Conclusions

4.1. Summary of findings

This paper introduced TRVF+, a tiered tri-phase resilience valuation framework that integrates preparedness, continuity, and restoration performance with monetized intangible-origin impacts in a CBA-compatible structure. Across four anonymized pilot cases, incorporating resilience effects and avoided disruption impacts increased baseline BCR values (0.88–1.15) to resilience-adjusted ratios RABCR (1.10–1.45). Monetized intangible benefits accounted for 15–30% of total benefits on average (up to ~40% within Tier-1 uncertainty bounds). Reporting both expected RABCR and Pr(RABCR>1.0) provided a transparent characterization of uncertainty and supported a robustness-based acceptance rule.

4.2. Importance and future work

By connecting operational resilience indicators and stakeholder-facing proxies to a monetized, uncertainty-aware decision metric, TRVF+ supports auditable appraisal and clearer communication of why resilience investments may remain justified under uncertainty. The tiered implementation logic reduces barriers to adoption by allowing organizations to start with expert judgement and progressively improve calibration as data maturity grows.

Future work should refine sector-specific calibration guidance, strengthen external validation across more cases, and investigate how political and institutional contexts influence the stability of monetization parameters and stakeholder response functions over time.

Author contribution

Yuri Chernenko: study conception and design, draft preparation; Olena Borodina: data collection, analysis and interpretation of results, proofreading and editing. All authors approved the final version of the manuscript.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

Funding information

No funding was received from any financial organization to conduct this research.

Ethical approval statement

The study used organizational operational records and aggregated, anonymized customer-feedback indicators (e.g., complaint counts and trust/satisfaction proxies) provided by participating organizations. Expert elicitation through structured Delphi panels involved organizational personnel who participated in their professional capacity. Oral informed consent was obtained regarding the use of their anonymized judgements for research purposes. No personally identifiable information was collected or processed. Formal ethical review was not required under the organizations' internal policies for anonymized, aggregate operational analytics and professional expert consultation.

Informed consent

Informed consent for the publication of personal data is not applicable because the manuscript contains no identifiable personal data. For Tier 1 expert elicitation, oral informed consent was obtained from all participants for the use of their anonymized judgements for research purposes.

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