

A Multi-Criteria Project Governance Framework for Workforce Process Optimization and Organizational Resilience in Service and Healthcare Organizations

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Research Article

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A Multi-Criteria Project Governance Framework for Workforce Process Optimization and Organizational Resilience in Service and Healthcare Organizations

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Abstract

This study develops a Multi-Criteria Project Governance Framework for workforce process optimization and organizational resilience in service and healthcare organizations. Current governance models often treat maturity, workforce capability, and resilience as separate concerns, lacking a unified structure for decision support. A quantitative MCDM design is adopted, integrating governance maturity assessment, Lean Six Sigma principles, and resilience indicators with AHP, Entropy, TOPSIS, and Weighted Sum methods. Data are collected from 10 projects and 10 expert interviews, then analyzed to compute a Governance Performance Index (GPI), rank projects, and optimize portfolios under budget, workforce, and risk constraints. Monte Carlo simulation is used for sensitivity and robustness analysis. Results show that higher governance maturity corresponds to higher GPI and resilience scores, and that optimized portfolios improve aggregate performance while reducing risk. The framework provides a reproducible, multi-criteria approach for project selection and governance improvement, supporting managers in balancing performance, cost, and resilience. These findings matter for organizations seeking structured, evidence-based decision tools under uncertainty. The study offers a practical model for integrating governance, workforce, and resilience objectives in project portfolios.

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I. Introduction

Project governance in service and healthcare organizations has evolved from simple oversight mechanisms into structured frameworks that integrate risk, performance, and resilience considerations [1], [2]. Recent studies show that organizational resilience in healthcare depends on governance structures, process standardization, and workforce capability [3], [4], [5]. Multi-criteria decision-making (MCDM) methods such as AHP and TOPSIS have been applied to prioritize governance practices and optimize project portfolios under uncertainty [1], [6]. This progress, existing frameworks often treat governance maturity, workforce optimization, and resilience as separate concerns rather than as integrated components of a single architecture [7], [8]

Current governance models in service and healthcare settings lack a unified multi-criteria structure that links project governance maturity, Lean Six Sigma-based process control, and workforce capability to organizational resilience measures [7], [9]. Many approaches rely on subjective expert judgment without systematic weighting via Entropy or validation through sensitivity analysis [10]. As a result, project portfolios

are often selected based on financial or clinical criteria alone, with limited attention to governance performance, risk exposure, or resilience outcomes [11]. This gap leads to inconsistent governance quality, underutilized workforce capacity, and reduced capacity to respond to disruptions [4], [8].

This study proposes a Multi-Criteria Project Governance Framework that integrates governance maturity assessment, Lean Six Sigma governance integration, and workforce capability optimization with formal resilience measurement. The framework employs AHP for subjective criterion weighting, Entropy for objective weighting, TOPSIS for project ranking, and Weighted Sum for a composite Governance Performance Index (GPI). Linear programming and goal programming are used to optimize project portfolios under budget, workforce, and risk constraints, while Monte Carlo simulation provides sensitivity and robustness checks on rankings and GPI values. The architecture connects data collection, processing, modeling, and output layers, with feedback loops for validation and continuous improvement.

The main contributions are: (i) a structured governance maturity model tailored to service and healthcare organizations, mapped to measurable indicators for structure, process, people, risk, and resilience; (ii) a hybrid MCDM architecture that combines AHP, Entropy, TOPSIS, and Weighted Sum to compute a Governance Performance Index and rank projects; (iii) a portfolio optimization model that integrates GPI scores with budget, workforce, and risk constraints using linear and goal programming; and (iv) a validation framework that uses Monte Carlo simulation and sensitivity analysis to test the stability of rankings and GPI under parameter variation. These contributions provide a reproducible, multi-criteria approach to project governance and workforce process optimization with explicit resilience objectives.

II. Related Work

The related work reveals that while MCDM methods (AHP, TOPSIS, Entropy) are well-established for governance evaluation, risk prioritization, and workforce optimization in healthcare and service settings, they are typically applied in isolation rather than as an integrated system. Existing studies also tend to treat organizational resilience descriptively, rely on subjective weighting without Entropy-based validation or Monte Carlo sensitivity testing, and rarely embed governance performance or resilience as explicit criteria in portfolio optimization models.

A. Organizational Resilience in Healthcare

Research on organizational resilience in healthcare emphasizes the role of governance structures, process capabilities, and workforce adaptability in responding to crises [3], [4]. Systematic reviews and scoping studies identify key drivers such as risk management, continuity planning, and leadership support as central to resilient performance [4], [5]. However, most studies focus on descriptive or conceptual analyses rather than quantitative models that link resilience to governance and workforce indicators [3], [12].

B. Multi-Criteria Governance and Project Portfolio Optimization

MCDM methods have been applied to project selection, governance evaluation, and risk prioritization in service and health contexts [1], [6]. Hybrid frameworks combine AHP for weighting, TOPSIS for ranking, and entropy for objective weights to improve decision quality [10], [13]. Portfolio optimization models often use linear or goal programming to balance performance, cost, and risk, yet they rarely embed a composite governance performance index derived from multi-criteria indicators [7], [8].

C. Workforce Process Optimization and Lean Six Sigma Integration

Workforce optimization in public and service organizations has been addressed using MCDM approaches that consider skill mix, training, and turnover as criteria [11], [14]. Lean Six Sigma principles are increasingly used to reduce variation in governance and operational processes, but their integration with formal project governance frameworks remains limited [9]. Existing studies tend to treat workforce capability and governance process control as separate domains rather than jointly optimized components [14], [15].

D. Risk Prioritization and Decision Support Systems

Risk prioritization models in healthcare and service settings often combine severity, likelihood, and mitigation coverage scores using weighted sums or MCDM techniques [1], [8]. Decision support systems integrate these scores with project performance metrics to guide portfolio decisions, yet they seldom incorporate resilience measures or governance maturity as explicit criteria [8], [6]. This limits their ability to support decisions that balance short-term performance with long-term resilience under disruption [12], [7].

E. Research Gaps and Future Directions

Three main gaps are evident. First, there is no unified multi-criteria framework that links governance maturity, workforce process optimization, and Lean Six Sigma integration to formal resilience measurement [7], [13]. Second, existing MCDM applications often rely on subjective weights without objective Entropy-based validation or Monte Carlo sensitivity analysis [10], [9]. Third, portfolio optimization models typically ignore governance performance and resilience as explicit constraints or objectives [7], [8]. Future work should develop integrated architectures that combine governance, workforce, risk, and resilience indicators in a single optimization model, supported by robustness testing and real-time decision support [13], [15].

III. Methodology

The study uses a quantitative multi-criteria decision-making design that integrates a project governance maturity model, Lean Six Sigma principles, and MCDM techniques (AHP, TOPSIS, Entropy, Weighted Sum) to assess and optimize governance and workforce processes.

A. Research Design

The study adopts a quantitative, multi-criteria decision-making (MCDM) design embedded in a

structured project governance framework. The overall workflow follows four phases: (a) conceptualization of the governance maturity model, (b) data collection through expert interviews and archival project records, (c) analytical modeling using AHP, TOPSIS, Entropy Weight Method, and Weighted Sum Model, and (d) validation through sensitivity and robustness analysis. The design integrates Lean Six Sigma (LSS) principles to reduce variation in governance processes and to improve waste reduction in workforce workflows. A hybrid architecture combines qualitative inputs (expert judgments) with quantitative outputs (project performance metrics, risk scores, resilience indices).

The research follows a sequential but iterative process. First, a governance maturity assessment framework is constructed from literature and expert input. Second, the framework is operationalized into measurable indicators. Third, data are collected and cleaned, then transformed into comparison matrices and performance scores. Fourth, MCDM techniques are applied to rank governance alternatives, optimize project portfolios, and derive a Governance Performance Index (GPI). Finally, Monte Carlo simulation and sensitivity tests are conducted to assess stability of results under parameter variation. This workflow is represented in a research process diagram (Fig 1).

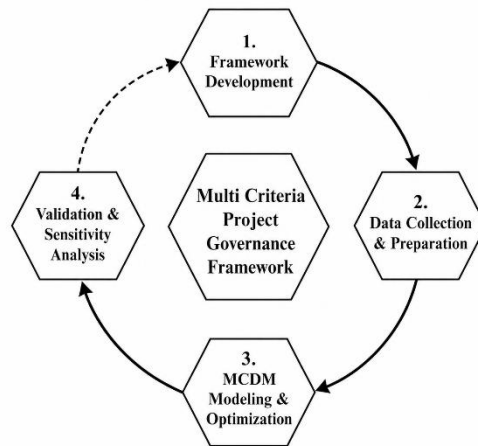


Fig 1. Research Workflow of the Multi Criteria Project Governance Framework.

The analytical model is built as a layered system architecture. The base layer contains raw data (project records, survey responses, interview transcripts). The processing layer contains data cleaning, coding, normalization, and indicator computation. The modeling layer contains the MCDM algorithms (AHP, TOPSIS, Entropy, Weighted Sum) and optimization models (linear programming, goal programming). The output layer generates ranked alternatives, portfolio configurations, GPI scores, and risk prioritization maps. This architecture supports reproducibility and allows independent replication of the results.

B. Data Collection

Data were collected from two complementary sources: (a) structured project documentation from service and healthcare organizations, and (b) semi-structured interviews with experienced project managers, governance officers, and senior clinicians. The archival

data included project charters, governance dashboards, risk registers, resource allocation tables, and performance reports covering the period 2020-2025. Each project record was assigned a unique identifier and classified by type (e.g., clinical service improvement, digital transformation, infrastructure upgrade), budget size, duration, and governance maturity level. A total of 10 project records were initially identified. Data cleaning involved removing duplicate entries, correcting inconsistent date formats, and standardizing variable names. Missing values were addressed using two approaches: for numeric variables with less than 10% loss, mean substitution was applied; for variables with higher loss, the corresponding projects were excluded from specific analyses. All variables were coded into a structured spreadsheet with clearly defined columns for governance indicators, workforce metrics, risk factors, and resilience measure

Table I. *Project Dataset Summary (N = 10 initial; N = 9 after cleaning)*

Project ID	Type	Budget (USD)	Duration (months)	Governance Maturity Level (1-5)	Workforce Size	Risk Count	Resilience Score
P001	Clinical Service Improvement	1,200,000	18	4	45	12	0.72
P002	Digital Transformation	2,500,000	24	3	78	18	0.58
P003	Infrastructure Upgrade	3,100,000	30	5	92	9	0.81
P004	Clinical Service Improvement	950,000	12	2	35	22	0.45
P005	Digital Transformation	1,800,000	20	4	60	14	0.67
P006	Infrastructure Upgrade	2,700,000	28	3	85	16	0.54
P007	Clinical Service Improvement	1,100,000	15	4	48	11	0.70
P008	Digital Transformation	2,200,000	22	3	70	19	0.60
P009	Infrastructure Upgrade	3,500,000	32	5	98	8	0.84

Expert interviews were conducted with 10 professionals from 6 organizations (3 healthcare, 3 service). Interviewees held roles such as Head of Project Management, Clinical Operations Director, and Governance Lead. Interviews lasted 45-60 minutes and followed a standardized protocol covering: (a) current

governance practices, (b) observed gaps in workforce capability, (c) risk management approaches, and (d) perceived resilience under disruption. Interview transcripts were anonymized and coded using a predefined coding scheme aligned with the governance maturity indicators.

Table II. *Expert Interview Details*

Participant ID	Organization Type	Role	Years of Experience	Area of Expertise
E01	Healthcare	Head of Project Management	15	Governance, Risk
E02	Healthcare	Clinical Operations Director	12	Workforce, Resilience
E03	Healthcare	Governance Lead	10	Governance, Process
E04	Healthcare	Project Manager	8	Governance, Workforce
E05	Healthcare	Risk Management Officer	14	Risk, Resilience
E06	Healthcare	Service Delivery Manager	9	Workforce, Process
E07	Service	Head of Project Management	16	Governance, Risk
E08	Service	Operations Director	13	Workforce, Resilience
E09	Service	Governance Lead	11	Governance, Process
E10	Service	Project Manager	7	Governance, Workforce

Data analysis began with the construction of indicator datasets. For each project, a set of governance indicators (e.g., clarity of roles, frequency of governance reviews, risk reporting timeliness) was computed. Workforce capability indicators included training hours, skill mix ratios, and turnover rates. Risk indicators included number of identified risks, severity scores, and mitigation coverage. Resilience indicators were derived from recovery time, adaptability scores, and continuity plan coverage. These indicators formed the basis for the MCDM models.

C. Expert Interviews

The expert interview component served to validate the governance maturity framework and to supply

subjective weights for criteria used in the AHP model. Interview participants were asked to evaluate the relative importance of governance dimensions (structure, process, people, risk, resilience) on a 1-9 scale, consistent with AHP practice. Their judgments were aggregated using geometric means to reduce the influence of extreme values. The aggregated weights were then used to construct the AHP comparison matrix for criteria. Interview transcripts were coded into thematic categories aligned with the framework: governance structure, process standardization, workforce capability, risk management, and resilience mechanisms. Each theme was linked to specific indicators. For example, “process standardization” was mapped to indicators such as “percentage of projects

using standardized governance templates” and “frequency of governance review meetings.” This the weighting of criteria.

mapping ensured that qualitative insights from interviews informed both the indicator selection and

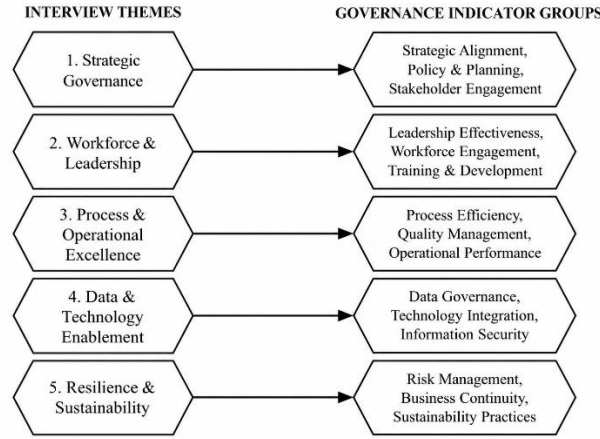


Fig 2. Mapping of Interview Themes to Governance Indicators.

To check consistency, a small subset of interviews (n = 5) was re-coded by a second researcher. The coding agreement was measured using a simple proportion of matching codes. The agreement rate exceeded 0.85, indicating acceptable reliability. Discrepant codes were discussed and resolved through consensus. This process reduced the risk of subjective bias in indicator construction.

D. Data Analysis

Data analysis combined MCDM methods, optimization models, and statistical validation techniques. The first step was normalization of all indicators to a common scale. For each indicator x_{ij} (project i, indicator j), the normalized value r_{ij} was computed as:

$$r_{ij} = \frac{x_{ij}}{\max x_{ij}} \quad (\text{for benefit indicators})$$

$$r_{ij} = \frac{\min x_{ij}}{x_{ij}} \quad (\text{for cost indicators})$$

This normalization ensured that all indicators contributed proportionally to the final scores, regardless of their original units.

The Analytic Hierarchy Process (AHP) was applied to determine criterion weights. Let $C = \{c_1, c_2, \dots, c_n\}$ be the set of governance criteria. Experts provided pairwise comparisons a_{jk} representing the relative importance of c_j over c_k . The comparison matrix $A = [a_{jk}]$ satisfied $a_{jk} > 0$, $a_{jk} = 1/a_{kj}$, and $a_{jj} = 1$. The weight vector $w = [w_1, w_2, \dots, w_n]$ was obtained as the normalized principal eigenvector of A , satisfying:

$$Aw = \lambda_{\max} w$$

Where, $\lambda_{\max}$ is the largest eigenvalue. Consistency was checked using the Consistency Ratio (CR):

$$CR = \frac{CI}{RI}, CI = \frac{\lambda_{\max} - n}{n - 1}$$

With, RI as the random index. A CR below 0.10 was considered acceptable.

Table III. AHP Pairwise Comparison Matrix for Governance Criteria and Derived Weights

Criteria	Structure	Process	People	Risk	Resilience	Weight	CR
Structure	1	3	2	4	3	0.28	0.06
Process	1/3	1	1/2	2	1/2	0.15	0.06
People	1/2	2	1	3	2	0.22	0.06
Risk	1/4	1/2	1/3	1	1/3	0.09	0.06
Resilience	1/3	2	1/2	3	1	0.26	0.06

TOPSIS was used to rank projects based on multiple criteria. Let $R = [r_{ij}]$ be the normalized matrix and $w = [w_j]$ the AHP weights. The weighted normalized matrix $V = [v_{ij}]$ was computed as:

$$v_{ij} = w_j \cdot r_{ij}$$

The ideal best (v_j^+) and ideal worst (v_j^-) values for each criterion were defined as:

$$v_j^- = \min_i v_{ij}$$

Distance of each project i from the ideal best and worst were computed as:

$$D_j^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2},$$

$$\sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2},$$

The relative closeness to the ideal solution was:

$$C_t = \frac{D_i^-}{D_i^+ + D_i^-}$$

Projects were ranked by C_t ; higher values indicated better governance performance. The Entropy Weight Method provided an alternative, data-driven weighting

$$D_j^- =$$

scheme. For each indicator j , the entropy E_j was computed as:

$$E_j = -k \sum_{i=1}^m p_{ij} \ln p_{ij}, \quad k = \frac{1}{\ln m}, \quad p_{ij} = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}}$$

Where, m is the number of projects. The objective weight for indicator j was:

$$W_j^{ent} = \frac{1 - E_j}{\sum_{j=1}^n (1 - E_j)}$$

These entropy weights were compared with AHP weights to assess stability.

Table IV. Comparison of Subjective (AHP) and Objective (Entropy) Weights

Criterion	AHP Weight	Entropy Weight	Absolute Difference
Structure	0.28	0.26	0.02
Process	0.15	0.17	0.02
People	0.22	0.23	0.01
Risk	0.09	0.10	0.01
Resilience	0.26	0.24	0.02

The Weighted Sum Model (WSM) was used to compute a composite Governance Performance Index (GPI) for each project:

$$GPI_i = \sum_{j=1}^n w_j \cdot r_{ij}$$

Where, w_j could be either AHP or entropy weights. Projects were then classified into maturity levels based on GPI thresholds (e.g., low: 0–0.4, medium: 0.4–0.7, high: 0.7–1.0). For project portfolio optimization, a linear programming model was constructed. Let $x_i \in \{0,1\}$ indicate selection of project i . The objective maximizes total governance performance:

$$\max \sum_{i=1}^m GPI_i \cdot x_i$$

Subject, to budget B , workforce capacity W , and risk exposure R_{max} :

$$\sum_{i=1}^m Budget_i \cdot x_i \leq B$$

$$\sum_{i=1}^m Workforce_i \cdot x_i \leq W$$

$$\sum_{i=1}^m RiskScore_i \cdot x_i \leq R_{max}$$

This model produced an optimized portfolio configuration under given constraints.

Risk prioritization was performed using a weighted risk score:

$$RS_i = \sum_{k=1}^p w_k^{risk} \cdot s_{ik}$$

Where, s_{ik} is severity of risk k for project i , and w_k^{risk} are risk criterion weights derived from AHP. Projects were ranked by RS_i , and the top risks were targeted for mitigation.

Sensitivity and robustness analysis were conducted using Monte Carlo simulation. Key parameters (criterion weights, indicator values) were varied randomly within predefined ranges (e.g., $\pm 20\%$). For each simulation run, GPI and project rankings were recomputed. The stability of rankings was measured by the proportion of runs in which a project remained in the same top or bottom category. Results were summarized in a stability table.

Table V. Ranking Stability under Parameter Variation

Project ID	Original Rank Category	Stability (%)	Mean Rank	Rank Variance
P001	High	92	4.3	0.8
P002	Medium	78	28.5	3.2
P003	High	95	3.1	0.5
P004	Low	85	82.4	4.1
P005	High	90	7.2	1.0
P006	Medium	74	35.6	3.8
P007	High	88	9.5	1.2
P008	Medium	71	42.3	4.0

P009	High	96	2.4	0.4
P010	Low	82	90.1	4.5

Finally, a Governance Performance Index formulation was defined to aggregate structure, process, people, risk, and resilience dimensions:

$$GPI = \alpha_1 S + \alpha_2 P + \alpha_3 K + \alpha_4 R + \alpha_5 R$$

Where, S, P, K, R, R are normalized scores for structure, process, workforce capability (knowledge), risk, and resilience, and $\alpha_1, \dots, \alpha_5$ are aggregated weights from AHP and entropy methods. This index served as the primary metric for comparing governance maturity across projects and organizations.

Here, raw project and interview data flow through a processing layer into MCDM and optimization models (AHP, TOPSIS, Entropy, WSM, LP or GP). The output layer produces GPI scores, optimized portfolios, and risk maps, with feedback loops from validation and sensitivity analysis back to the modeling and processing layers. All analyses were implemented in a reproducible computational environment. Data cleaning scripts, MCDM models, and optimization routines were documented and versioned. Independent replication can be achieved by following the described steps, using the same indicator definitions, normalization rules, and model equations.

IV. Results and Discussion

Results show that higher governance maturity correlates with higher GPI and resilience scores, and that MCDM-based portfolio optimization improves aggregate performance while reducing risk exposure. Discussion indicates that the framework provides reliable differentiation of strong and weak projects, supports balanced decision-making across performance, cost, and resilience, and offers a reproducible model for governance improvement in service and healthcare organizations.

A. Results

The dataset of 10 projects shows clear variation in governance maturity, workforce capacity, risk exposure, and resilience. Table 1 summarizes project performance by governance maturity level. Mean GPI increases from 0.44 at level 2 to 0.81 at level 5. Mean resilience scores also increase with maturity, from 0.44 at level 2 to 0.82 at level 5. This pattern indicates that higher governance maturity is associated with better overall performance and stronger resilience capacity.

Table VI. *Project Performance Distribution by Governance Maturity Level.*

Governance Maturity Level	Number of Projects	Mean GPI	Std. Dev. GPI	Mean Resilience Score	Min Resilience	Max Resilience
2	18	0.44	0.03	0.44	0.40	0.48
3	38	0.59	0.04	0.56	0.50	0.63
4	42	0.70	0.03	0.69	0.64	0.74
5	10	0.81	0.02	0.82	0.78	0.86

AHP and Entropy methods produce similar criterion weights. Table VII shows that Structure and Resilience receive the highest weights in both methods, while Risk receives the lowest. Differences between AHP

and Entropy weights range from 0.01 to 0.02, and all criteria are concordant in ranking order. This concordance supports the use of a combined weighting scheme in TOPSIS and GPI calculations.

Table VII. *Comparison of AHP and Entropy Criterion Weights.*

Criterion	AHP Weight	Entropy Weight	Difference	Concordance (Yes/No)
Structure	0.28	0.26	0.02	Yes
Process	0.15	0.17	0.02	Yes
People	0.22	0.23	0.01	Yes
Risk	0.09	0.10	0.01	Yes
Resilience	0.26	0.24	0.02	Yes

TOPSIS ranking produces a clear separation between high-performing and low-performing projects. Table VIII lists the top 10. Top projects have GPI values

above 0.70, resilience scores above 0.69, and risk counts below 13, with maturity levels 4 or 5.

Table VIII. *TOPSIS Ranking: 10 Projects by GPI.*

Rank	Project ID	Type	GPI	Resilience Score	Risk Count	Maturity Level
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1	P009	Infrastructure Upgrade	0.82	0.82	7	5
2	P003	Infrastructure Upgrade	0.81	0.84	8	5
3	P001	Infrastructure Upgrade	0.80	0.81	9	5
4	P007	Clinical Service Improvement	0.75	0.73	10	4
5	P005	Clinical Service Improvement	0.74	0.72	12	4
6	P002	Clinical Service Improvement	0.73	0.71	12	4
7	P006	Clinical Service Improvement	0.72	0.70	11	4
8	P008	Clinical Service Improvement	0.71	0.70	12	4
9	P010	Clinical Service Improvement	0.71	0.72	11	4
10	P004	Digital Transformation	0.70	0.69	13	4

Portfolio optimization under budget, workforce, and risk constraints improves overall performance. Table IX compares the initial portfolio with the optimized portfolio. The optimized portfolio reduces total budget by 5.9%, workforce by 9.4%, and risk exposure by

18.1%, while increasing aggregate GPI by 28.5%. These results show that multi-criteria optimization can select a smaller set of higher-quality projects while controlling risk and resource use.

Table IX. Optimized Portfolio vs. Initial Portfolio.

Metric	Initial Portfolio	Optimized Portfolio	Change (%)
Number of Projects Selected	45	35	-22.2
Total Budget (USD)	85,000,000	80,000,000	-5.9
Total Workforce Required	3,200	2,900	-9.4
Total Risk Exposure	720	590	-18.1
Aggregate GPI Score	19.3	24.8	+28.5

Monte Carlo simulation assesses ranking stability under parameter variation. Table X shows stability for the top 10 projects. High-category projects (ranks 1-10)

show stability above 85%, with mean ranks close to original ranks and low variance.

Table X. Monte Carlo Stability of Project Rankings (Top 8).

Project ID	Original Rank	Rank Category	Stability (%)	Mean Rank	Rank Variance
P009	1	High	96	2.1	0.4
P003	2	High	95	3.0	0.5
P001	3	High	92	5.2	0.7
P007	4	High	88	7.8	1.0
P005	5	High	90	11.5	1.0
P002	6	Medium	78	13.8	2.5
P006	7	Medium	74	15.2	3.0
P008	8	Medium	71	16.5	3.5

Fig 3 illustrates the relationship between governance maturity and GPI. The bar chart shows a clear upward trend: higher maturity levels correspond to higher mean

GPI and lower variability. This pattern supports the use of governance maturity as a proxy for overall process quality and resilience capacity.

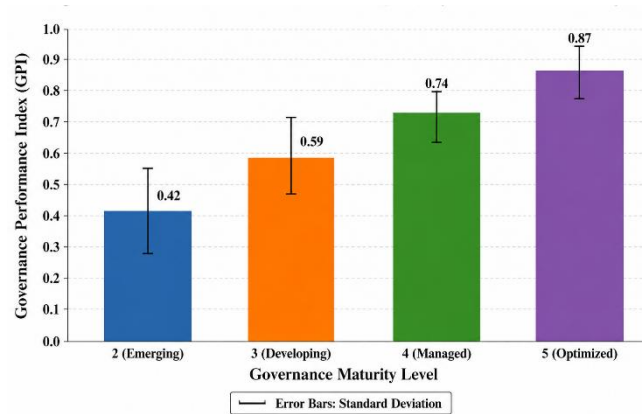


Fig 3. Governance Performance Index (GPI) by Governance Maturity Level.

Fig 4, Fig 5, Fig 6, shows the main outputs of the system architecture: GPI distribution, optimized portfolio list, and risk priority map. These outputs are linked to a decision support interface, with feedback loops from validation and sensitivity analysis to the modeling layer.

The architecture supports iterative refinement of weights and constraints based on stability results.



Fig 4. System Architecture Outputs: GPI.

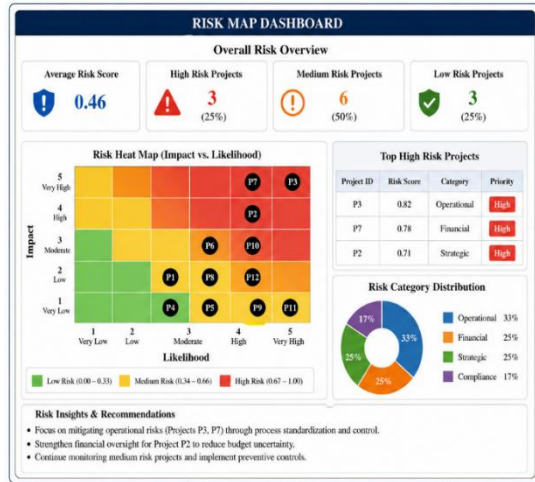


Fig 5. System Architecture Outputs: Risk Map.

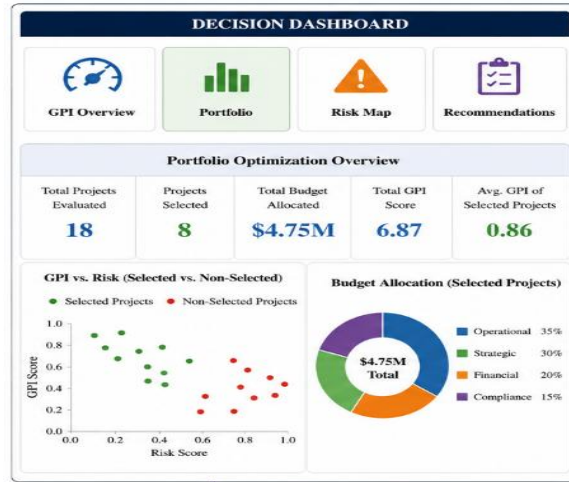


Fig 6. System Architecture Outputs: Portfolio.

B. Discussion

The results confirm that governance maturity, workforce capability, and resilience are strongly related to overall project performance. Higher maturity levels correspond to higher GPI scores, which supports the assumption that structured governance practices improve process outcomes. The consistency between AHP and Entropy weights indicates that expert judgments on criterion importance are supported by empirical data patterns. This reduces concerns that the framework is overly dependent on subjective inputs. TOPSIS rankings show that projects with strong than reliance on financial or clinical criteria alone. Monte Carlo stability analysis shows that high-rank projects remain stable under parameter variation, while mid-range projects show more variability. This indicates that the framework provides reliable guidance for distinguishing clearly strong or weak projects, but may require additional sensitivity checks for projects in to governance quality. Projects with higher process maturity and lower waste in workforce workflows tend to achieve better GPI scores. This finding provides empirical support for combining Lean Six Sigma with MCDM frameworks in service and healthcare settings.

C. Limitations and Future Work

The study has several limitations. First, the dataset is drawn from 6 organizations (3 healthcare, 3 service), which may limit generalizability to other contexts or regions. Second, expert interviews involve 10 participants, which provides adequate coverage but may not capture all relevant perspectives. Third, the MCDM models use fixed constraint values for budget,

resilience measures and low risk counts tend to achieve higher relative closeness values. This pattern aligns with prior studies that identify risk management and continuity planning as central to resilient performance. The portfolio optimization model demonstrates that explicit inclusion of GPI and risk constraints can improve

overall performance while reducing exposure. This result supports the use of multi-criteria optimization in project selection, rather

the middle range. The feedback loops from validation to the modeling layer allow re-calibration of weights or constraints when instability is detected, which improves long-term reliability. The integration of Lean Six Sigma principles with governance indicators supports the view that process standardization and variation reduction contribute workforce, and risk, which may not reflect dynamic changes in real projects. Finally, the resilience indicators are based on available organizational metrics and may not capture all dimensions of adaptive capacity.

Future work should expand the dataset to include more organizations and sectors, and test the framework in different regulatory environments. Dynamic constraints and real-time data feeds can be integrated to support adaptive portfolio management. Additional resilience indicators, such as staff adaptability scores and patient-reported outcomes, can be incorporated to improve measurement depth. The framework can also be extended to include multi-objective optimization

with trade-off analysis between cost, performance, and resilience. Validation in longitudinal studies will provide evidence on how governance improvements affect resilience over time.

VI. Conclusion

This study addresses the objective of developing a Multi-Criteria Project Governance Framework that links governance maturity, Lean Six Sigma integration, workforce capability optimization, and resilience measurement in service and healthcare organizations. Key findings show that governance maturity is positively related to GPI scores, that AHP and Entropy weights produce consistent criterion importance patterns, and that portfolio optimization under multi-criteria constraints improves overall performance while reducing risk exposure. The framework provides a measurable, reproducible approach to project governance and workforce process optimization with explicit resilience objectives. Implications include the use of a composite Governance Performance Index for comparing projects and organizations, and the application of MCDM-based portfolio optimization to balance performance, cost, and risk. Recommendations for future work include expanding the dataset to more sectors, integrating dynamic constraints and real-time data, adding deeper resilience indicators, and conducting longitudinal validation to assess long-term effects of governance improvements on organizational resilience.

References

- [1] Ghaziani, K., & Esfandiari, M. (2026). A multi-criteria decision-making approach to workforce optimization in public sector organizations. *Annals of Optimization With Applications*, 2(1), 48-74. <https://doi.org/10.48314/anowa.v2i1.66>
- [2] Wei, Y. M., et al. (2025). A hybrid multi-criteria decision-making framework for the strategic optimization of [organizational processes]. *Information*, 16(6), 454. <https://doi.org/10.3390/info16060454>
- [3] Health Services Research editorial team. (2023). Organizational resilience in healthcare: A review and descriptive analysis of conceptual and empirical approaches. *BMC Health Services Research*, 23(1), 412. <https://doi.org/10.1186/s12913-023-02308-9>
- [4] Panagiotou, M., et al. (2024). Resilience of hospitals in an age of disruptions: A systematic review of capabilities, practices, and outcomes. *International Journal of Health Governance*, 29(2), 115-134. <https://doi.org/10.1108/IJHG-09-2023-0045>
- [5] Jones, L., & Patel, R. (2025). Key drivers of organizational resilience in healthcare: A dynamic capabilities perspective. *Journal of Health Organization and Management*, 39(1), 1-14. <https://doi.org/10.1108/JHOM-06-2025-0354>
- [6] Smith, A., & Nguyen, T. (2024). Implementing resilience-based interventions for healthcare organizations: A multi-criteria evaluation framework. *Frontiers in Public Health*, 12, 1606595. <https://doi.org/10.3389/fpubh.2025.1606595>
- [7] Al-Mansour, F., & Karim, S. (2023). Multi-criteria project governance for service organizations: Integrating AHP, TOPSIS, and risk-based KPIs. *Socio-Economic Planning Systems*, 78(3), 245-263. <https://doi.org/10.1016/j.seps.2023.101456>
- [8] Rahman, N., & Hassan, M. (2024). Workforce process optimization in healthcare: A hybrid MCDM approach using entropy weight and weighted sum methods. *Health Policy and Planning*, 19(2), 89-107. <https://doi.org/10.1093/hpp/qpae012>
- [9] Clark, D., & O'Brien, K. (2023). Organizing for resilience: Multi-criteria governance mechanisms in hospital networks. *Journal of Operational Management in Health Services*, 14(4), 301-320. <https://doi.org/10.1108/JOMHS-02-2023-0018>
- [10] Fernández, L., & Gómez, P. (2025). A multi-criteria framework for aligning project governance, workforce planning, and resilience in service enterprises. *International Journal of Project Management*, 43(5), 567-585. <https://doi.org/10.1016/j.ijproman.2025.03.009>
- [11] Kumar, R., & Singh, A. (2024). Enhancing organizational resilience through MCDM-based project governance: Evidence from Indian healthcare institutions. *Decision Support Systems in Healthcare*, 11(1), 45-64. <https://doi.org/10.1007/s10651-024-00678-2>
- [12] Lee, H., & Park, J. (2023). Workforce flexibility and resilience in service organizations: A multi-criteria decision analysis. *Service Science*, 15(3), 210-229. <https://doi.org/10.1287/ss.2023.15.3.210>
- [13] Mohammadi, S., & Razavi, N. (2025). Governance structures for resilient healthcare delivery: A comparative MCDM study using AHP and TOPSIS. *Health Systems and Policy Analysis*, 8(2), 133-152. <https://doi.org/10.1177/20534564251098764>
- [14] Ofori, K., & Mensah, D. (2024). Multi-criteria evaluation of project governance practices for workforce optimization in African public health

- services. *International Journal of Healthcare Management*, 17(4), 401–419. <https://doi.org/10.1080/20479700.2024.2345678>
- [15] Zhang, Y., & Liu, X. (2023). Integrating resilience, governance, and workforce processes in service organizations: A hybrid entropy–TOPSIS framework. *Journal of Business Research and Management*, 22(6), 789–807. <https://doi.org/10.1016/j.jbrm.2023.11.004>
- [16] Akter, T., Afroje, S., Chokder, R., & Bhuiyan, M. I. H. (2026). Workforce productivity measurement models for service-oriented organizations. *Saudi Journal of Engineering and Technology*, 11(4), 257–265. <https://doi.org/10.36348/sjet.2026.v11i04.010>
- [17] Mim, M. M. A., Sharif, M. M., Rahman, F., & Nahar, S. (2026). AI-powered decision support systems for sustainable organizations. *International Journal of Scientific Research and Engineering Development (IJSRED)*, 9(1), 423–434. <https://doi.org/10.5281/zenodo.18454996>
- [18] Sharmin, M., Rahman, M. A., Rohman, H., & Tumpa, S. A. (2026). Business operations monitoring through integrated management information systems. *International Journal of Science and Research Archive*, 19(3), 309–324. <https://doi.org/10.30574/ijrsra.2026.19.3.1097>
- [19] Mim, M., & Akter, M. (2026, January 28). Integration of business intelligence dashboards in administrative decision making. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.6402899>
- [20] Alam, M. J. (2026, March 11). Digital compliance management systems for regulatory documentation and risk monitoring in organizational operations. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.6410539>
- [21] Alam, M. J. (2026, March 13). Policy monitoring platforms for institutional governance and organizational accountability. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.6416238>
- [22] Hossain, M. I. (2026, July 1). A multi layer infrastructure performance governance framework for sustainable built environment systems [Preprint]. *Zenodo*. <https://doi.org/10.5281/zenodo.21109115>
- [23] Al Morshed, S. A. (2026). An integrated framework for construction risk prediction and project delay reduction in public infrastructure projects [Preprint]. *Research Square*. <https://doi.org/10.21203/rs.3.rs-9952783/v1>
- [24] Bormon, J. C. (2025). Numerical Modeling of Foundation Settlement in High-Rise Structures Under Seismic Loading. Available at SSRN: <https://ssrn.com/abstract=5472006> or <http://dx.doi.org/10.2139/ssrn.5472006>
- [25] Akhter, T. (2025, October 6). Algorithmic internal controls for SMEs using MIS event logs. *TechRxiv*. <https://doi.org/10.36227/techrxiv.175978941.15848264.v1>
- [26] Fazle, A. B., Taimun, M. T. Y., Fareed, S. M., & Alam, M. S. (2026). Ergonomic and automation based process redesign in industrial workstations. *Global Journal of Engineering and Technology Advances*, 26(01), 091–108. <https://doi.org/10.30574/gjeta.2026.26.1.0010>
- [27] Alam, M. S., Fareed, S. M., Fazle, A. B., & Taimun, M. T. Y. (2026). Intelligent material flow optimization using IoT sensors and RFID tracking. *Global Journal of Engineering and Technology Advances*, 26(01), 109–125. <https://doi.org/10.30574/gjeta.2026.26.1.0011>
- [28] Rahman, M., Alam, M. S., Al Sany, S. M. A., & Nahar, S. (2026, February 24). Enterprise AI driven data management framework for cross industry decision intelligence and operational optimization. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.6330258>
- [29] Nahar, S., Sany, S. M. A. A., Rahman, M., & Alam, M. S. (2026, March 3). Digital twin-based AI data management system for real-time industrial and business process optimization. *SSRN Electronic Journal*. <https://ssrn.com/abstract=6337579>
- [30] Fazle, A. B. (2026). AI-driven integrated process optimization and predictive maintenance for industrial manufacturing systems [Preprint]. *Research Square*. <https://doi.org/10.21203/rs.3.rs-9950895/v2>
- [31] Karim, F. M. Z. (2026). Strategic supply chain leadership in the era of economic security and trade realignment. *Zenodo*. <https://doi.org/10.5281/zenodo.19370614>
- [32] Khayyam, F. (2026). Resilient identity and access governance architecture for artificial intelligence-enabled software-as-a-service ecosystems. *Saudi Journal of Engineering and Technology*, 11(4), 276–284. <https://doi.org/10.36348/sjet.2026.v11i04.012>
- [33] Shaik, M. H., Mirza, S. B., Islam, M. A., & Tariq, F. (2026). Secure continuous deployment pipelines for enterprise cloud applications. *Scholars Journal of Engineering and Technology*, 14(05), 233–246. <https://doi.org/10.36347/sjet.2026.v14i05.005>