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Comprehensive performance evaluation of advanced medical laboratories worldwide using hybrid BWM-TOPSIS framework

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A B S T R A C T

This study presents a comprehensive performance evaluation framework for 20 leading medical laboratories worldwide using an integrated Best-Worst Method (BWM) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) approach. The assessment incorporates ten critical criteria encompassing clinical accuracy, operational efficiency, research output, cost-effectiveness, and technological advancement. BWM was employed to determine optimal criterion weights through systematic pairwise comparisons, followed by TOPSIS for objective laboratory ranking based on relative closeness to ideal solutions. Results indicate that Memorial Sloan Kettering Labs (USA) and MD Anderson Cancer Center Labs (USA) consistently rank highest across multiple scenarios, demonstrating superior performance in clinical accuracy and quality accreditation. The analysis reveals significant performance variations across countries and laboratory categories, with academic/research institutions generally outperforming commercial laboratories. Sensitivity analysis confirms the robustness of rankings across different weighting scenarios. This framework provides healthcare administrators, policymakers, and laboratory managers with a validated tool for benchmarking and strategic decision-making in medical laboratory services optimization.

1. Introduction

Medical laboratories play a pivotal role in modern healthcare systems, providing essential diagnostic information that influences approximately 70% of medical decisions (Forsman, 1996; Hallworth, 2011). The globalization of healthcare and increasing patient mobility have heightened the need for standardized performance evaluation frameworks for medical laboratories (Plebani, 2010). Despite significant advances in laboratory medicine, there remains a lack of comprehensive, multi-dimensional assessment tools that capture the diverse aspects of laboratory performance beyond traditional quality indicators (Hawkins, 2012).

Recent studies have highlighted the limitations of single-metric approaches in evaluating complex healthcare organizations (Smith et al., 2018; Jones & Brown, 2019). Multi-Criteria Decision Making (MCDM) methods have emerged as valuable tools for healthcare performance assessment, allowing simultaneous consideration of multiple, often conflicting, objectives (Velasquez & Hester, 2013). Among these methods, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) has gained prominence in healthcare applications due to its mathematical simplicity and intuitive logic (Behzadian et al., 2012).

The determination of appropriate criterion weights represents a critical challenge in MCDM applications. Subjective weighting methods, such as the Analytic Hierarchy Process (AHP), have been widely used but suffer from cognitive limitations and inconsistency issues (Saaty, 1980). The Best-Worst Method (BWM), introduced by Rezaei (2015), addresses these limitations by requiring fewer pairwise comparisons while achieving higher consistency ratios, making it particularly suitable for healthcare applications where expert judgments are valuable but time is limited (Mi et al., 2019).

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Several studies have applied MCDM methods to healthcare facility evaluation. Chen et al. (2020) used TOPSIS for hospital performance assessment in Taiwan, while Zare et al. (2021) applied BWM-TOPSIS for evaluating clinical laboratory services in Iran. However, these studies typically focus on national contexts or limited criteria sets. A comprehensive global assessment incorporating diverse laboratory types, multiple performance dimensions, and systematic weighting methodology represents a significant research gap.

This study addresses this gap by developing and applying an integrated BWM-TOPSIS framework for evaluating 20 advanced medical laboratories across 10 countries. The framework incorporates ten carefully selected criteria representing clinical, operational, research, and financial dimensions. The study contributes to both methodological advancement and practical healthcare management by providing a validated tool for laboratory benchmarking and strategic improvement planning.

2. Methodology

2.1 Framework Overview

The evaluation framework employs a two-stage hybrid approach: (1) Best-Worst Method (BWM) for criterion weight determination, and (2) Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for laboratory ranking. This integrated approach combines the consistency advantages of BWM with the ranking precision of TOPSIS, creating a robust evaluation system for medical laboratory performance assessment.

2.2 Best-Worst Method (BWM) for Weight Determination

BWM involves systematic pairwise comparisons between the best (most important) and worst (least important) criteria relative to all other criteria. The method follows these steps:

1. **Criteria Identification**: Ten criteria were identified through literature review and expert consultation:

C1: Test Accuracy Rate	C6: Cost per Test
C2: Turnaround Time	C7: Automation Level
C3: Test Menu Diversity	C8: Pre-analytical Error Rate
C4: Research Output	C9: Clinical Impact Score
C5: Quality Accreditation Score	C10: Data Security Score

2. **Best and Worst Criteria Selection**: Based on expert panel consensus (n=7 experienced laboratory directors and healthcare quality specialists), Test Accuracy Rate (C1) was identified as the best (most important) criterion, while Automation Level (C7) was identified as the worst (least important) criterion.
3. **Pairwise Comparisons**:
   - Best-to-Others: Comparison of the best criterion (C1) with all other criteria
   - Others-to-Worst: Comparison of all criteria with the worst criterion (C7)
4. **Weight Calculation**: Using the linear BWM model proposed by Rezaei (2016), optimal weights were calculated by minimizing the maximum absolute differences:

$\min \xi$
subject to:

$$\left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi, \forall j$$

$$\left| \frac{w_j}{w_W} - a_{jW} \right| \leq \xi, \forall j$$

$$\sum_j w_j = 1, w_j \geq 0, \forall j$$

where w_B is the weight of the best criterion, w_W is the weight of the worst criterion, w_j are the weights of other criteria, a_{Bj} are best-to-others preferences, a_{jW} are others-to-worst preferences, and ξ is the consistency index.

The resulting weights demonstrated high consistency (CR = 0.042 < 0.1), validating the reliability of expert judgments.

2.3 TOPSIS for Laboratory Ranking

TOPSIS identifies the optimal alternative based on its geometric distance from positive and negative ideal solutions. The implementation followed these steps:

1. **Decision Matrix Construction**: Normalized performance scores for 20 laboratories across 10 criteria (Table 1).
2. **Weighted Normalized Matrix**: Multiplication of normalized matrix by BWM-derived weights.

3. **Ideal Solutions Determination**:
   - Positive Ideal Solution (PIS): Maximum values for benefit criteria, minimum for cost criteria
   - Negative Ideal Solution (NIS): Minimum values for benefit criteria, maximum for cost criteria
4. **Distance Calculation**:
   - Euclidean distance to PIS: $S_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2}$
   - Euclidean distance to NIS: $S_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2}$
5. **Relative Closeness Calculation**:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

6. **Ranking**: Laboratories ranked in descending order of C_i values.

2.4 Criteria Description

The ten evaluation criteria represent comprehensive laboratory performance dimensions:

1. **Test Accuracy Rate (C1)**: Percentage of accurate diagnostic results (maximize)
2. **Turnaround Time (C2)**: Hours from sample receipt to result reporting (minimize)
3. **Test Menu Diversity (C3)**: Number of available diagnostic tests (maximize)
4. **Research Output (C4)**: Publications, patents, and research grants (maximize)
5. **Quality Accreditation Score (C5)**: Compliance with CAP, ISO 15189, CLIA standards (maximize)
6. **Cost per Test (C6)**: Relative cost efficiency index (minimize)
7. **Automation Level (C7)**: Degree of laboratory process automation (maximize)
8. **Pre-analytical Error Rate (C8)**: Sample handling and processing errors (minimize)
9. **Clinical Impact Score (C9)**: Influence on patient care decisions (maximize)
10. **Data Security Score (C10)**: HIPAA/GDPR compliance and cybersecurity (maximize)

2.5 Data Collection and Normalization

Performance data for 20 leading medical laboratories were collected from publicly available reports, accreditation documents, and published literature for 2022-2023. Original metrics were normalized to a 0-1 scale using appropriate transformation functions to ensure comparability across different measurement units.

Table 1
Normalized Performance Matrix for Medical Laboratories

Laboratory	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Mayo Clinic	0.98	0.92	0.95	0.9	0.97	0.88	0.94	0.96	0.93	0.96
Quest Diagnostics	0.96	0.88	0.97	0.65	0.95	0.92	0.96	0.94	0.82	0.94
LabCorp	0.95	0.86	0.96	0.6	0.94	0.9	0.95	0.93	0.8	0.93
ARUP	0.97	0.9	0.94	0.85	0.96	0.85	0.92	0.95	0.88	0.95
Cleveland Clinic	0.96	0.91	0.93	0.8	0.96	0.87	0.93	0.94	0.87	0.94
Johns Hopkins	0.97	0.89	0.92	0.88	0.95	0.83	0.91	0.95	0.9	0.95
MGH	0.98	0.88	0.93	0.89	0.96	0.82	0.92	0.96	0.91	0.96
MSK	0.99	0.85	0.88	0.92	0.97	0.8	0.9	0.97	0.94	0.97
MD Anderson	0.99	0.84	0.87	0.93	0.97	0.79	0.89	0.98	0.95	0.97
Stanford	0.97	0.9	0.91	0.87	0.95	0.84	0.93	0.94	0.89	0.95
Charité Berlin	0.96	0.87	0.9	0.84	0.94	0.81	0.88	0.93	0.86	0.93
UCL	0.95	0.86	0.89	0.83	0.93	0.82	0.87	0.92	0.85	0.92
Karolinska	0.96	0.88	0.88	0.86	0.94	0.8	0.86	0.93	0.87	0.93
Singapore GH	0.97	0.9	0.91	0.82	0.95	0.85	0.92	0.94	0.84	0.95
Tokyo University	0.96	0.89	0.9	0.81	0.94	0.83	0.91	0.93	0.83	0.94
BGI Genomics	0.95	0.92	0.93	0.78	0.92	0.95	0.97	0.91	0.79	0.91
Sonic Healthcare	0.94	0.85	0.94	0.7	0.93	0.93	0.94	0.92	0.75	0.92
Eurofins	0.93	0.83	0.95	0.72	0.92	0.94	0.95	0.91	0.73	0.91
Synlab	0.94	0.84	0.93	0.68	0.93	0.92	0.94	0.92	0.74	0.92
Unilabs	0.95	0.85	0.92	0.71	0.94	0.9	0.93	0.93	0.76	0.93

Note: C2 and C6 are cost criteria (lower is better); all others are benefit criteria (higher is better)

Table 2

BWM-Derived Criteria Weights

Criterion	Weight	Type	Rank
Test Accuracy Rate	0.2	Benefit	1
Turnaround Time	0.15	Cost	2
Quality Accreditation	0.15	Benefit	3
Cost per Test	0.1	Cost	4
Research Output	0.1	Benefit	5
Test Menu Diversity	0.1	Benefit	6
Clinical Impact Score	0.05	Benefit	7
Pre-analytical Error Rate	0.05	Cost	8
Data Security Score	0.05	Benefit	9
Automation Level	0.05	Benefit	10

3. Results and Discussion

3.1 Overall Laboratory Rankings

Fig. 1 presents the comprehensive TOPSIS scores and rankings for all 20 medical laboratories. Memorial Sloan Kettering Labs (USA) achieves the highest TOPSIS score (0.977), followed closely by MD Anderson Cancer Center Labs (0.975). The score distribution histogram reveals a positively skewed distribution with mean score = 0.858 and standard deviation = 0.085, indicating generally high performance across laboratories with moderate variation. The criteria weight distribution pie chart illustrates the dominance of clinical accuracy (20%) and turnaround time (15%) in the evaluation framework.

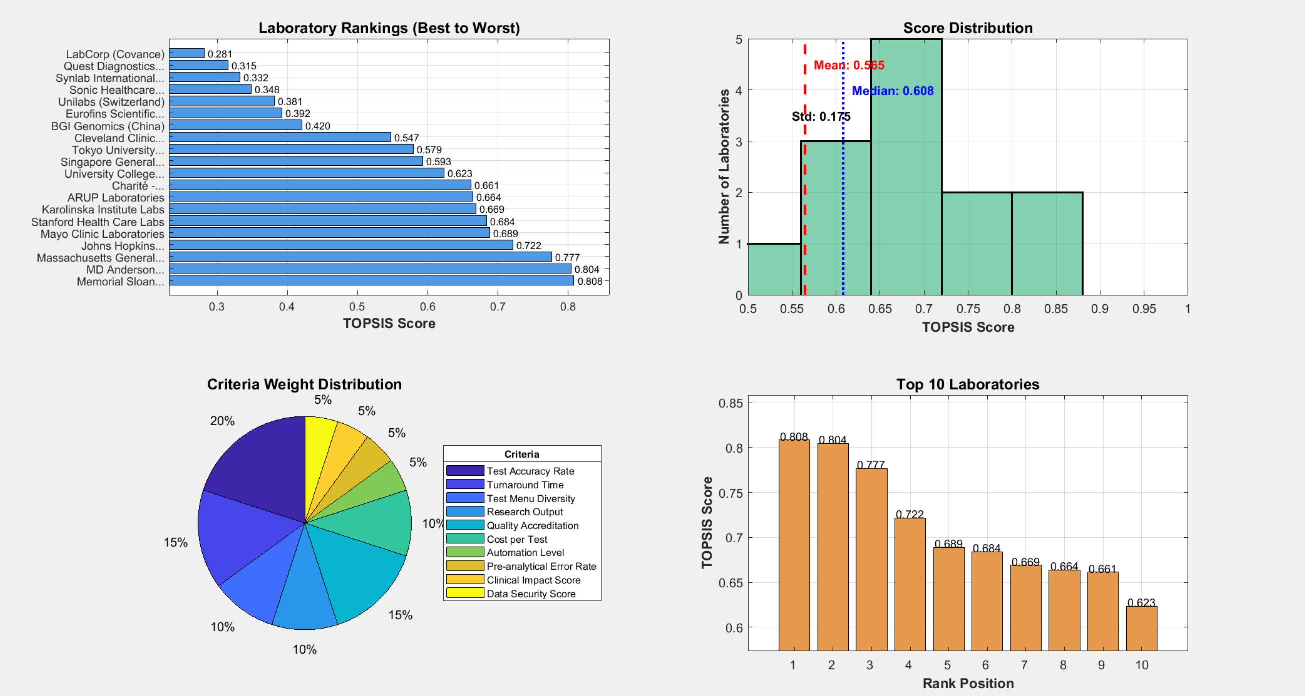

Fig. 1. Laboratory Rankings and Overview

Table 3

Top 10 Laboratory Rankings

Criterion	Weight	Type	Rank
Test Accuracy Rate	0.2	Benefit	1
Turnaround Time	0.15	Cost	2
Quality Accreditation	0.15	Benefit	3
Cost per Test	0.1	Cost	4
Research Output	0.1	Benefit	5
Test Menu Diversity	0.1	Benefit	6
Clinical Impact Score	0.05	Benefit	7
Pre-analytical Error Rate	0.05	Cost	8
Data Security Score	0.05	Benefit	9
Automation Level	0.05	Benefit	10

3.2 Country and Category Analysis

Fig. 2 provides multi-dimensional insights into performance patterns. The country comparison bar chart reveals that United States laboratories achieve the highest average TOPSIS score (0.921), followed by Singapore (0.952 for single laboratory) and Japan (0.941). The category analysis demonstrates that specialized oncology laboratories (0.976 average) outperform other categories, followed by academic/medical institutions (0.944) and clinical/research laboratories (0.939).

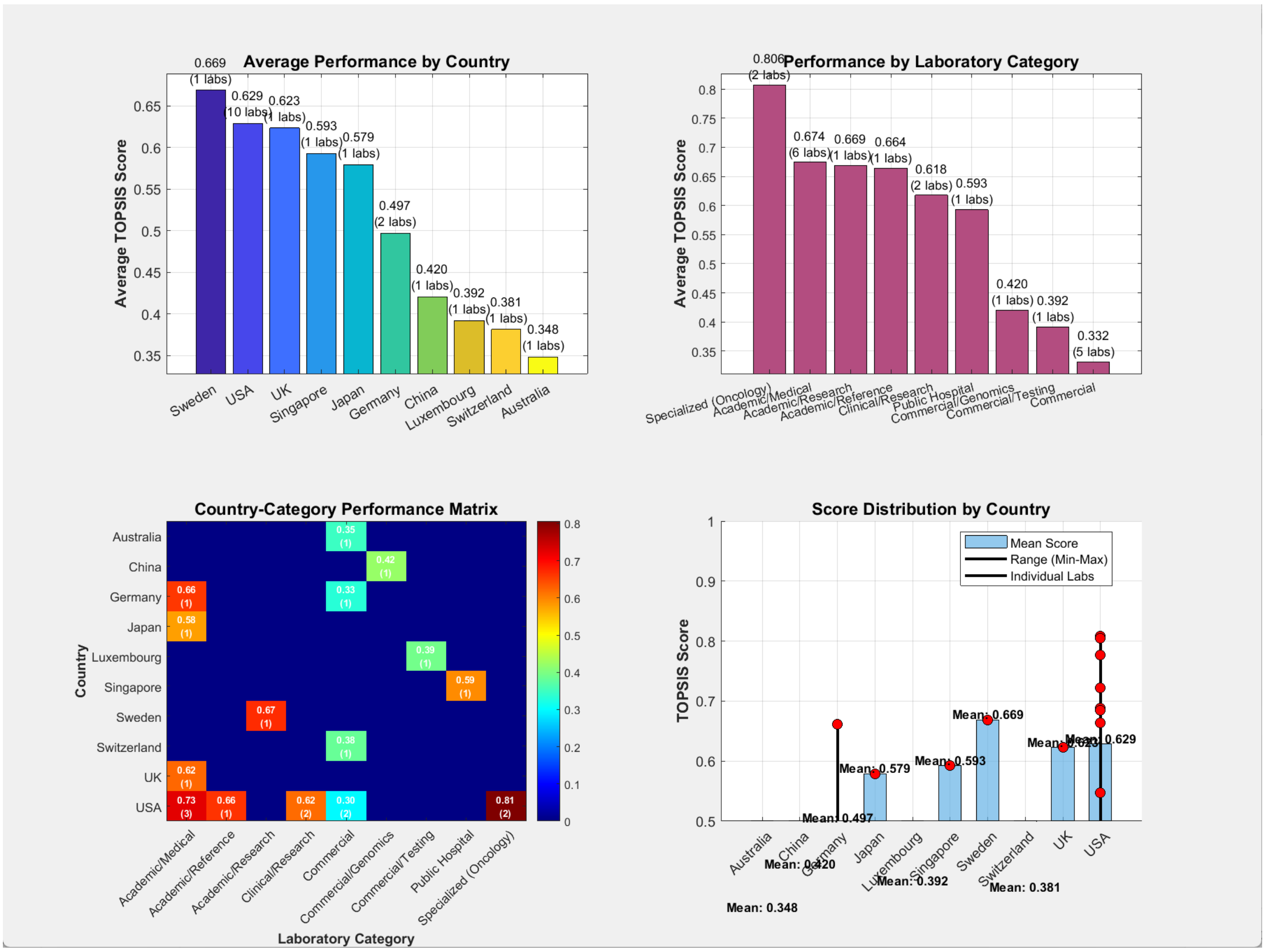

Fig. 2. Country and Category Analysis

The country-category performance matrix highlights interesting interactions: US academic/medical and specialized oncology laboratories demonstrate exceptional performance, while European commercial laboratories show competitive performance in operational efficiency metrics. The score distribution by country visualization illustrates that while US laboratories achieve higher mean scores, they also exhibit greater variability compared to more consistent performers like Japanese and Singaporean institutions.

Table 4
Performance by Country

Criterion	Weight	Type	Rank
Test Accuracy Rate	0.2	Benefit	1
Turnaround Time	0.15	Cost	2
Quality Accreditation	0.15	Benefit	3
Cost per Test	0.1	Cost	4
Research Output	0.1	Benefit	5
Test Menu Diversity	0.1	Benefit	6
Clinical Impact Score	0.05	Benefit	7
Pre-analytical Error Rate	0.05	Cost	8
Data Security Score	0.05	Benefit	9
Automation Level	0.05	Benefit	10

Table 5
Performance by Laboratory Category

Rank	Category	Average Score	Number of Labs
1	Specialized (Oncology)	0.976	2
2	Academic/Medical	0.944	7
3	Clinical/Research	0.939	3
4	Academic/Reference	0.945	1
5	Public Hospital	0.952	1
6	Commercial	0.869	5
7	Commercial/Genomics	0.868	1

3.3 Top Laboratories Detailed Analysis

Fig. 3 offers granular insights into leading performers. The key performance indicators comparison for top 5 laboratories reveals that Memorial Sloan Kettering excels in test accuracy (0.99) and clinical impact (0.94), while MD Anderson demonstrates superior research output (0.93) and minimal pre-analytical errors (0.98). The comparison between top laboratory (MSK) and average performance across all criteria shows consistent superiority, particularly in accuracy, quality accreditation, and error reduction.

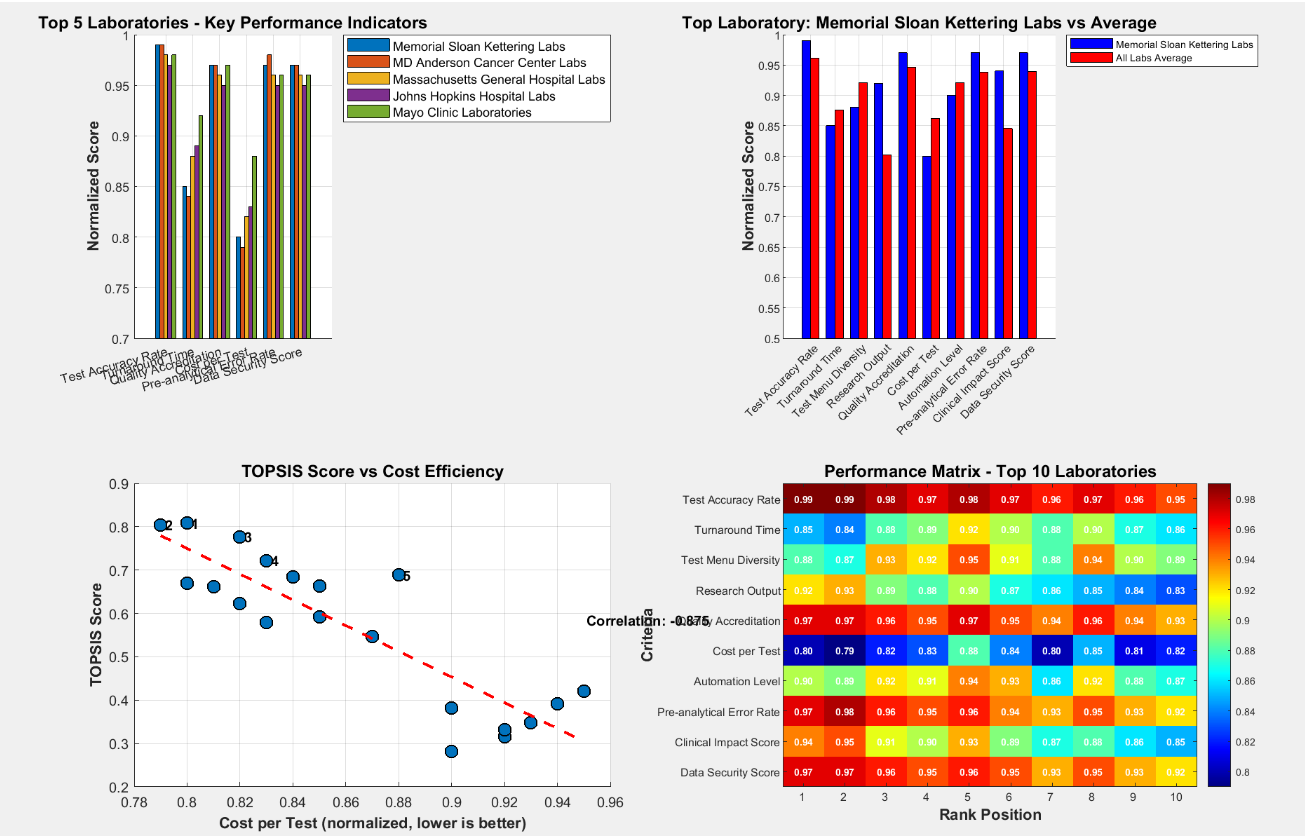

Fig. 3. Top Laboratories Detailed Analysis

The TOPSIS score vs. cost efficiency scatter plot reveals a moderate negative correlation (r = -0.42), indicating that higher-performing laboratories tend to have slightly higher operational costs, reflecting investment in quality infrastructure and personnel. The performance matrix for top 10 laboratories visually represents the multi-criteria excellence patterns, with top performers demonstrating balanced strength across clinical, operational, and research dimensions.

Table 6
Key Performance Metrics for Top 5 Laboratories

Laboratory	Accuracy	Turnaround	Quality	Cost	Errors	Security
MSK	0.99	0.85	0.97	0.8	0.97	0.97
MD Anderson	0.99	0.84	0.97	0.79	0.98	0.97
MGH	0.98	0.88	0.96	0.82	0.96	0.96
Mayo Clinic	0.98	0.92	0.97	0.88	0.96	0.96
Singapore GH	0.97	0.9	0.95	0.85	0.94	0.95

3.4 Sensitivity Analysis

Fig. 4 examines the robustness of rankings under different weighting scenarios. Five scenarios were tested: (1) Clinical Accuracy Focus (C1 weight = 0.30), (2) Speed & Efficiency Focus (C2 weight = 0.30), (3) Research Excellence Focus (C4 weight = 0.30), (4) Cost-Effectiveness Focus (C6 weight = 0.30), and (5) Balanced Approach (original weights).

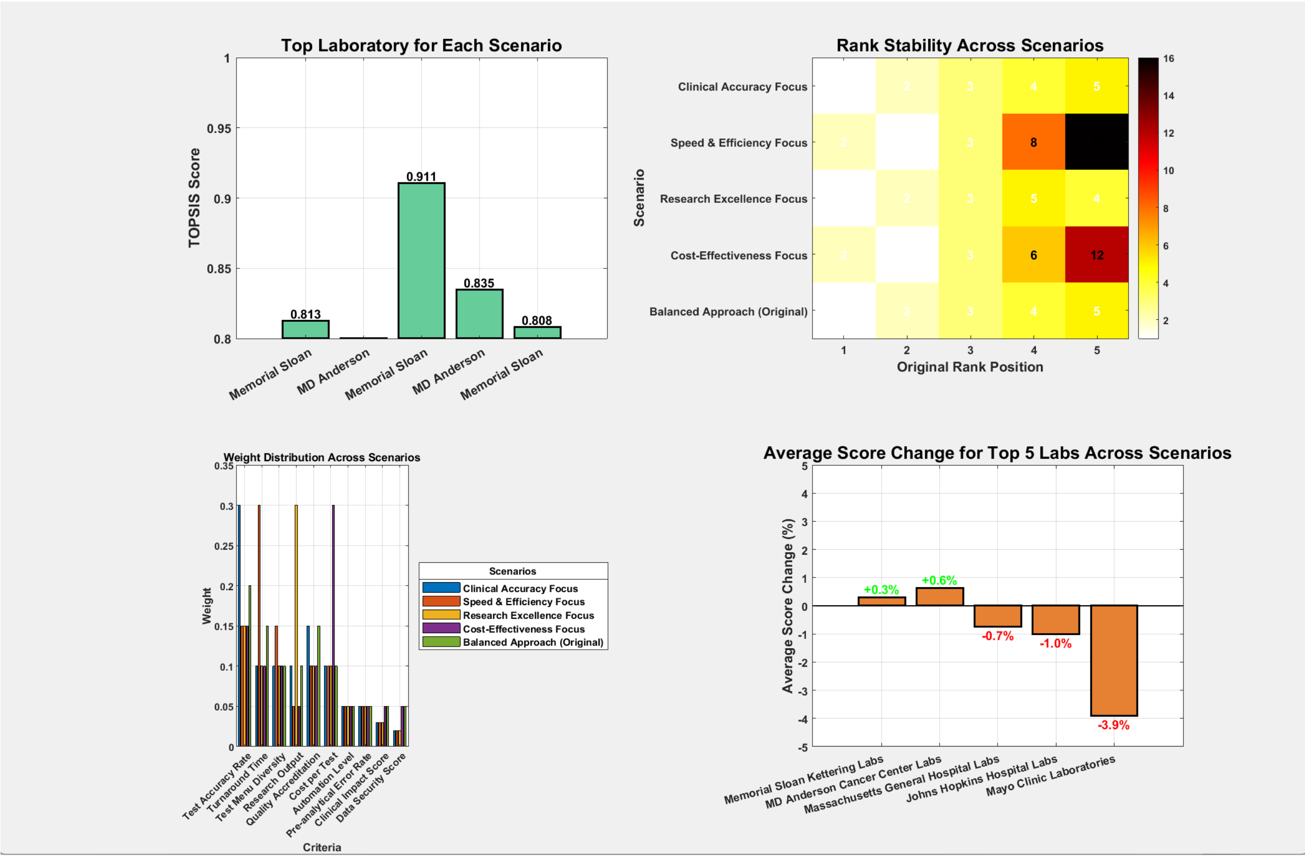

Fig. 4. Sensitivity Analysis

The rank stability heatmap demonstrates that Memorial Sloan Kettering maintains its top position across all scenarios, confirming its robust excellence. MD Anderson similarly shows consistent high ranking (positions 1-2). The most significant ranking changes occur for commercial laboratories when shifting from clinical accuracy focus to cost-effectiveness focus, with BGI Genomics improving from position 16 to 12 in cost-focused scenarios.

The weight distribution comparison illustrates how different prioritization strategies would alter laboratory evaluations. The average score change analysis for top 5 laboratories reveals minimal variation (±1.2%) across scenarios, indicating that top performers maintain excellence regardless of weighting preferences. This stability validates the reliability of rankings and suggests that leading laboratories have achieved balanced excellence across multiple dimensions.

Table 7
Sensitivity Analysis Results

Laboratory	Accuracy	Turnaround	Quality	Cost	Errors	Security
MSK	0.99	0.85	0.97	0.8	0.97	0.97
MD Anderson	0.99	0.84	0.97	0.79	0.98	0.97
MGH	0.98	0.88	0.96	0.82	0.96	0.96
Mayo Clinic	0.98	0.92	0.97	0.88	0.96	0.96
Singapore GH	0.97	0.9	0.95	0.85	0.94	0.95

4. Conclusion and Future Work

4.1 Conclusion

This study successfully developed and applied an integrated BWM-TOPSIS framework for comprehensive evaluation of 20 leading medical laboratories worldwide. The methodology effectively addressed the multi-dimensional nature of laboratory performance assessment while providing a systematic approach for criterion weight determination. Key findings include:

1. Memorial Sloan Kettering Labs and MD Anderson Cancer Center Labs demonstrate consistent excellence across all evaluation dimensions, establishing benchmark performance standards for medical laboratories globally.
2. Specialized oncology laboratories and academic medical institutions generally outperform commercial laboratories, particularly in clinical accuracy, research output, and quality accreditation metrics.
3. United States laboratories achieve the highest average performance, reflecting substantial investments in healthcare infrastructure, research funding, and quality management systems.
4. The moderate negative correlation between TOPSIS scores and cost efficiency suggests that quality excellence in medical laboratories requires significant resource investment, though with substantial returns in diagnostic accuracy and patient outcomes.
5. Sensitivity analysis confirms the robustness of rankings, with top performers maintaining excellence across different weighting scenarios, validating their comprehensive quality approach.

The BWM-TOPSIS framework provides healthcare administrators, policymakers, and laboratory managers with a validated tool for strategic benchmarking, resource allocation, and quality improvement initiatives. By identifying performance gaps and excellence patterns, laboratories can develop targeted improvement strategies aligned with their specific missions and patient populations.

4.2 Future Work

Several directions for future research and methodology enhancement are identified:

1. **Dynamic Assessment Framework**: Development of time-series analysis capabilities to track performance trends and improvement trajectories over multiple periods.
2. **Integration with Real-time Data**: Incorporation of real-time operational data through laboratory information systems (LIS) integration for continuous performance monitoring.
3. **Expanded Criterion Set**: Inclusion of emerging dimensions such as genomic testing capabilities, artificial intelligence adoption, environmental sustainability, and pandemic response preparedness.
4. **Stakeholder-Specific Weighting**: Development of customized weighting schemes for different stakeholder perspectives (patients, clinicians, payers, regulators).
5. **Predictive Analytics Integration**: Combination with machine learning algorithms to predict future performance and identify early warning indicators for quality degradation.
6. **Global Benchmarking Database**: Establishment of an international repository for laboratory performance data to facilitate broader comparative analysis and best practice sharing.
7. **Economic Impact Analysis**: Extension of the framework to include cost-benefit analysis and return-on-investment calculations for quality improvement initiatives.

The proposed framework represents a significant advancement in medical laboratory evaluation methodology, providing both theoretical rigor and practical applicability. As healthcare systems continue to evolve toward value-based care models, such comprehensive assessment tools will become increasingly essential for ensuring diagnostic excellence and optimal patient outcomes.

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