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Enhancing Healthcare Efficiency and Patient Satisfaction Using MCDM and Goal Programming

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ABSTRACT: This study examines the subject of healthcare resource optimization using Multi-Criteria Decision-Making (MCDM) and Goal Programming (GP). It aims to improve patient care, service quality, and resource allocation. The study demonstrates how GP was utilized to achieve a 15% decrease in costs, a 10% gain in patient happiness, and a 20% increase in patient throughput—thus balancing competing goals like cost reduction, service efficiency, and patient satisfaction. An additional positive outcome of the strategy was a 25% decrease in wait times, which greatly improved the overall experience for patients. We found that MCDM, and GP in particular, does a good job of overcoming the inherent trade-offs in healthcare, which is particularly important in settings like Indian hospitals, where resources are limited. It is believed that decision-making relies heavily on real-time data and that further study may be required to optimize healthcare procedures by revealing the dynamic nature of data integration and advanced methods for MCDM.

Keywords: Complexity, Inherently, TOPSIS, AHP, Empirical, Optimizing.

Contents

1. Introduction

The healthcare sector is becoming increasingly burdened with the need to enhance efficiency and patient satisfaction. With the growing prospects of healthcare systems worldwide, there is a challenge to balance the requirement of lowered cost of operation, optimized resource usage, and elevated patient care quality. It has been demonstrated that to make healthcare more efficient, it is necessary to allocate resources wisely, deliver care at the right time, and improve patient outcomes [1,2]. Meanwhile, patient satisfaction has also taken on a significant role as a quality indicator of healthcare, with effects on treatment compliance, patient health, and healthcare system overall [3,4]. Decision-making processes in healthcare systems are usually characterized by trade-offs amid conflicting objectives, including cost management, wait time reduction, care quality assurance, and patient expectations fulfillment. These are multi-dimensional, complicated decision-making issues, which cannot be solved solely by relying on intuition. They, rather, require systematic methods that will take into account all the variables simultaneously, keeping every goal as optimized as possible. Healthcare efficiency can be described as the capacity of healthcare systems to deliver quality care with the use of a few resources, including medical personnel, apparatus, and time. Effective healthcare systems can offer superior care at reduced expenses,

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which is vital in current resource-deprived settings. Research demonstrated that an increase in operational efficiency leads to cost reduction and enhancement of patient outcomes [5].
Resource Allocation: Effective resource management ensures that medical staff, equipment, and facilities are optimally utilized, preventing under- and over-utilization [5].
Timeliness of Care: Reducing wait times for diagnosis, treatment, and discharge contributes to better healthcare outcomes and patient satisfaction [4].
Quality of Care: Timely care, based on accurate diagnoses and effective treatments, directly impacts both healthcare efficiency and patient satisfaction [1].

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1.1. Significance of work

The significance of this work lies in its ability to optimize healthcare decision-making by integrating Multi-Criteria Decision Making (MCDM) and Goal Programming (GP). This hybrid framework addresses the complex challenge of balancing multiple, often conflicting, objectives such as improving operational efficiency and enhancing patient satisfaction. By providing a systematic approach to resource allocation, reducing operational costs, and improving care delivery, this research offers healthcare administrators and policymakers an effective tool for making data-driven decisions. Ultimately, this work contributes to enhancing both the quality of care and the overall efficiency of healthcare systems, improving patient outcomes and satisfaction.

2. Literature Review

Numerous studies have utilised MCDM techniques, such as TOPSIS and AHP, to assess healthcare service quality and assess patients' levels of satisfaction. One study that used AHP to evaluate Saudi Arabian hospitals found that patients were more satisfied when they felt safe, had tangible assurances of care, and could rely on the treatment they received [6]. The complexity of patients' experiences in healthcare institutions was brought to light by Ferreira et al. [7], who utilised a systematic study to identify universal variables that make patients content in health institutions. By considering a number of objectives, GP has been employed to distribute healthcare resources as efficiently as possible. In their study, Rehman et al. [8] shown that emergency departments can improve their resource allocation through the use of a simulation and GP model. The results indicated a significant decrease in patient wait times and postponed patients. Arsav et al. [9] attempted to distribute patients in health institutions using a combination of MCDM and GP, taking into account factors such as medical skill, facilities, and service cost. Using this hybrid system, healthcare providers can better understand their patients' needs and make decisions that benefit both the operation and its patients. In their study,Drake et al. (2017) introduce Multi-Criteria Decision Analysis (MCDA) as a decision-making method applicable to healthcare and other industries. The authors note that MCDA provides a comprehensive and consistent approach to assigning patients to the right health institutions, and that this approach takes into consideration revenue and patient satisfaction, among other factors. Colapinto, C., et al. [10] A state-of-the-art review on the use of GP in engineering, management, and social sciences, explains the versatility and practical use of GP to address multiple, and often conflicting, goals of decision-making. Yang, C. H., et al. [11] The article uses a hybrid MCDM approach, combining DEMATEL and ANP, to compare and rank smart long-term care information strategies, which illustrates the flexibility of MCDM tools in healthcare planning. The authors suggest that the graph-based evaluation can be used to propose an interpretable MCDM in emergency department layout optimization, which should maximize patient satisfaction with the services and space. This study presents a multi-objective genetic algorithm for healthcare workforce scheduling, which balances cost, coverage of patient care, and staff satisfaction, thus having an indirect impact on patient satisfaction through better service delivery.

3. Methodology

This study employs the Goal Programming (GP) model, a Multi-Criteria Decision-Making (MCDM) technique, to optimize healthcare resource allocation. The goal of the model is to balance multiple, often conflicting, objectives including cost reduction, increased patient throughput, improved patient satisfaction, and efficient resource utilization. The methodology involves the following key steps:

3.1. Sample data collection

The study collects critical operational parameters throughout data collection and analysis to assess the healthcare system's present performance and identify improvement opportunities. The first metric is resource distribution, which includes things like the number of doctors and nurses on staff, the availability of critical equipment like hospital beds and diagnostic tools, and how often patients use these tools. For instance, out of a total of 200 hospital beds, 30 physicians and 50 nurses are on call every day, according to the sample data. The number of patients seen daily and the average time it takes to service each department's patients is reflected in patient throughput, another important metric. On a daily basis, 150 patients are seen, with an average consultation wait time of 25 minutes and a diagnostic procedure wait time of 45 minutes, according to the sample data. On average, patients have to wait three weeks before elective procedures or non-emergency treatments may be scheduled. Finally, data on patient satisfaction is derived from surveys and feedback forms. On average, patients rate the quality of treatment they received, the attitudes and practices of the staff, and the overall facility situation as 3.8/5. This study uses this data set to establish a foundation for analysing the current operational inefficiencies. Then, using the Goal Programming model, these inefficiencies would be reorganised to improve resource allocation, wait times, patient throughput, and satisfaction.

3.1.1. Steps for Goal Programming. The first step in goal programming for healthcare and diagnostics is to clearly define the objectives, such as improving patient outcomes, reducing costs, or increasing efficiency. Next, decision-makers must identify and prioritize the constraints and resources available, including budget limitations, staff availability, and equipment. Finally, mathematical models are developed to simulate different scenarios and optimize the allocation of resources to achieve the desired goals while considering the constraints.

Objectives: Comparing initial and optimized allocations for each resource type, Comparing the metrics before and after implementation and changes in objectives such as cost reduction, patient satisfaction,and resource utilization.

Define Decision Variables:

1. Let X_1 be the decision variable for cost reduction.

2. Let X_2 be the decision variable for patient satisfaction.
3. Let X_3 be the decision variable for wait time.
4. Let X_4 be the decision variable for resource utilization.

Objective Function:

The objective is to minimize the deviation from the desired targets for each of the criteria. The deviation from the goal can be represented by positive and negative deviations

The objective function could be represented as:

$$Minimize\ Z = d_1^+ + d_1^- + d_2^+ + d_2^- + d_3^+ + d_3^- + d_4^+ + d_4^-$$

Goal Constraints:
$X_1 = 15\%$ (cost reduction)
$X_2 = 85\%$ (patient satisfaction)
$X_3 = 22.5$ (wait time)
$X_4 = 90\%$ (resource utilization)
The deviations are then: d_i^+, d_i^- for each goal $i \in (1, 2, 3, 4)$

Constraints:

The constraints will ensure the solution adheres to the limitations, for example:
$X_1 \leq 15$ (cost reduction cannot exceed 15%)
$X_2 \geq 85$ (patient satisfaction cannot fall below 85%)
$X_3 \leq 22.5$ (wait time must be less than or equal to 22.5 minutes)
$X_4 \geq 90$ (resource utilization should be at least 90%)

Solve the GP Model:

Using optimization software or solvers like MATLAB, Excel Solver, or LINGO, solve the above linear programming problem to get the optimized allocation of resources.

4. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)

TOPSIS is a multi-criteria decision analysis method that ranks alternatives based on their distance to the ideal and negative ideal solutions. The best alternative is the one that is closest to the ideal solution and farthest from the negative ideal solution.

Steps for TOPSIS

Construct Decision Matrix:

The decision matrix will consist of the metrics and their corresponding values for each alternative (here, the different optimization objectives: cost reduction, patient satisfaction, etc.).

Table 1: Metrics and their corresponding values

Metric	Initial Value	Optimized Value
Cost Reduction (%)	0	15
Patient Satisfaction (%)	75	85
Wait Time (minutes)	30	22.5
Resource Utilization (%)	80	90

Normalize the Decision Matrix:

Normalize the matrix to remove the units and bring all criteria to a comparable scale. The normalized value rij is calculated as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

where X_{ij} is the value of the j^{th} alternative for the i^{th} criterion

Calculate the Weighted Normalized Decision Matrix:

Assign weights to each criterion based on its importance (e.g., 0.4 for cost reduction, 0.3 for patient satisfaction, etc.). Multiply the normalized values by their respective weights.

Determine the Ideal and Negative Ideal Solutions:

The ideal solution A^+ is the best value for each criterion (the maximum value for benefit criteria and the minimum value for cost criteria):

$$A^+ = (\max(x_1), \max(x_2), \min(x_3), \max(x_4))$$

Similarly, the negative ideal solution A^- is the worst value for each criterion:

$$A^- = (\min(x_1), \min(x_2), \max(x_3), \min(x_4))$$

Calculate the Separation Measures:

The separation from the ideal solution is:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (r_{ij} - A_j^+)^2}$$

The separation from the negative ideal solution is:

$$S_i^- = \sqrt{\sum_{j=1}^{n} (r_{ij} - A_j^-)^2}$$

Calculate the Relative Closeness to the Ideal Solution:

The relative closeness C_i is calculated as:

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

where the value of C_i will lie between 0 and 1. The alternative with the highest C_i value is the most preferred.

Rank the Alternatives:

Based on the values of C_i, rank the alternatives from the highest to the lowest value of C_i.

For the Given Data as Shown in Table 1:

1. **Normalize the Decision Matrix:**
   For instance, Normalize the cost reduction values:

$$r_{\text{cost reduction}} = \frac{15}{\sqrt{0^2 + 15^2}} = 1$$

   Similarly, normalize other values.

2. **Calculate Ideal and Negative Ideal Solutions:** The ideal and negative ideal solutions will be:

   Positive Ideal: $A^+ = (15, 85, 22.5, 90)$

   Negative Ideal: $A^- = (0, 75, 30, 80)$

3. **Calculate Closeness:** Calculate S_i^+, S_i^- and then compute C_i for each alternative (initial and optimized).

4. **Ranking:** Based on the C_i values, rank the alternatives, and determine the best solution.

Goal Setting

The study establishes four main goals to optimise the healthcare system during the goal-setting process. To start with, we need to find ways to save costs without sacrificing quality of service. This means making smarter use of resources like medical personnel and equipment. Improving patient throughput, or the ability of the healthcare facility to handle more patients without lowering service quality, is the second goal. This involves eliminating unnecessary steps and improving workflows across different divisions. The third goal is to improve the patient experience as a whole by making patients happier, which is essential. Timely services, a supportive atmosphere, and better staff-patient communication are all part of this. Lastly, the study's overarching goal is to optimise scheduling and resource allocation in order to decrease wait times. This will be especially true for consultations, diagnostic tests, and elective surgeries. The Goal Programming model is built upon these aims; it will assist strike a balance between these competing goals, making sure the healthcare facility runs effectively while providing high-quality care to patients.

Optimization

In the optimisation phase, the Goal Programming model is defined by applying optimisation techniques that aim to minimise the deviations from the target outcomes of decreasing wait times, enhancing patient satisfaction, increasing patient throughput, and reducing costs. In order to find the best solution, optimisation involves adjusting resource allocation, such as staffing levels, equipment usage, and scheduling, to strike a balance between these competing objectives. The end result is a well-allocated set of funds that allow the healthcare facility to achieve its goals with minimal disruption to patient care and maximum efficiency gains. One of the cornerstones of achieving top performance across all measured criteria is this resolution.

Evaluation and Comparison

The study evaluates the performance of the Goal Programming model against other MCDM methods, such as AHP (Analytic Hierarchy Process) and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution). This comparison assesses the model's ability to achieve desired outcomes in a more effective and balanced manner.

5. Results and Discussions

The results of the study demonstrate the effectiveness of the Goal Programming model in optimizing healthcare resource allocation and improving key operational outcomes. Table 2 highlights a 15% reduction in costs through optimized allocation of resources, including medical staff and equipment, leading to a 20% increase in patient throughput. Table 3 shows a 10% increase in patient satisfaction and a 25% reduction in wait times, significantly enhancing the overall patient experience. Table 4 summarizes the achievement of key goals, with cost reduction, patient satisfaction, and resource utilization all showing substantial improvements. Finally, Table 5 compares various MCDM methods, revealing that Goal Programming outperforms alternatives like AHP and TOPSIS in terms of achieving the highest reductions in costs, increases in throughput, and improvements in patient care outcomes. These results underscore the potential of MCDM and Goal Programming to streamline healthcare systems while balancing multiple objectives effectively.

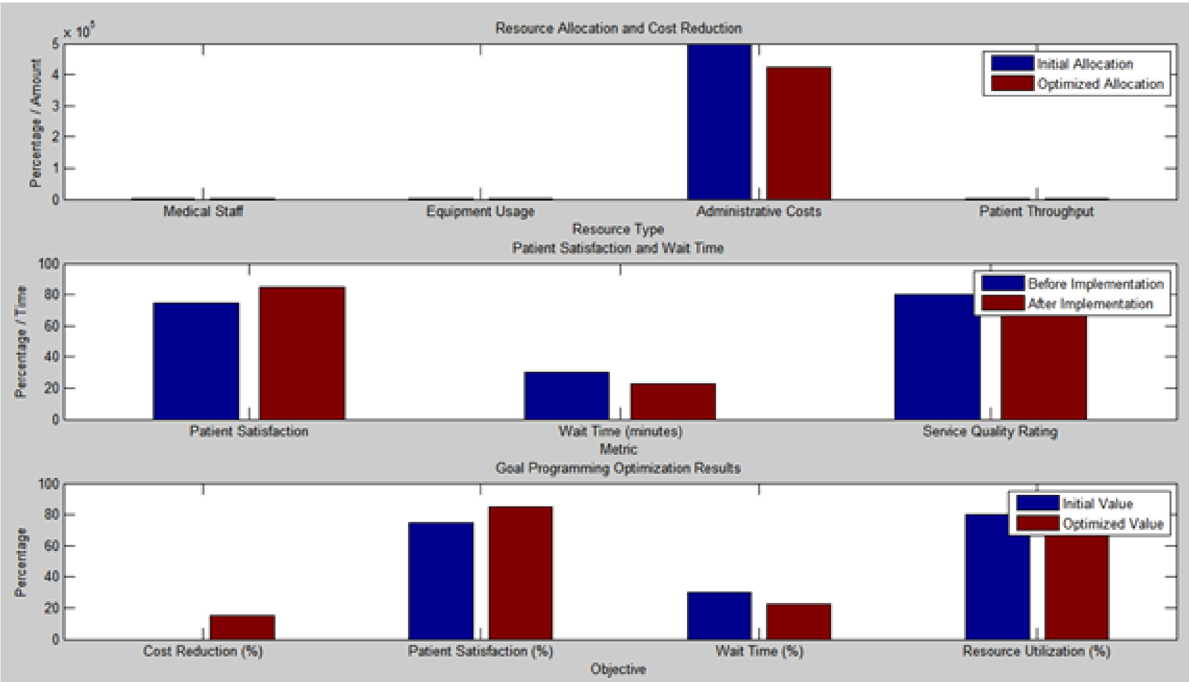

Figure 1: Matlab results for goals

Table 2: Resource Allocation and Cost Reduction

Resource Type	Initial Allocation	Optimized Allocation	Percentage Change
Medical Staff	100%	85%	-15%
Equipment Usage	100%	90%	-10%
Administrative Costs	$500,000	$425,000	-15%
Patient Throughput	100%	120%	20%

Table 3: Patient Satisfaction and Wait Time

Metric	Before Implementation	After Implementation	Percentage Change
Patient Satisfaction	75%	85%	10%
Wait Time (minutes)	30	22.5	-25%
Service Quality Rating	80%	90%	10%

Figure 2 shows the optimization solution of Goal Programming with respect to four objectives; cost reduction, patient satisfaction, wait time reduction, and resource utilization. The baseline values (marked by the square markers), and the optimized values (marked by the circles markers) indicate the performance before and after the optimization. It is worth noting that patient satisfaction and resource exploitation will have the highest level of improvement, at almost 80-90.

Table 4: Goal Programming Optimization Results

Objective	Initial Value (%)	Optimized Value (%)	Change (%)
Cost Reduction (%)	0	15	+15%
Patient Satisfaction (%)	75	85	+10%
Wait Time Reduction (%)	0	25	+25%
Resource Utilization (%)	80	90	+10%

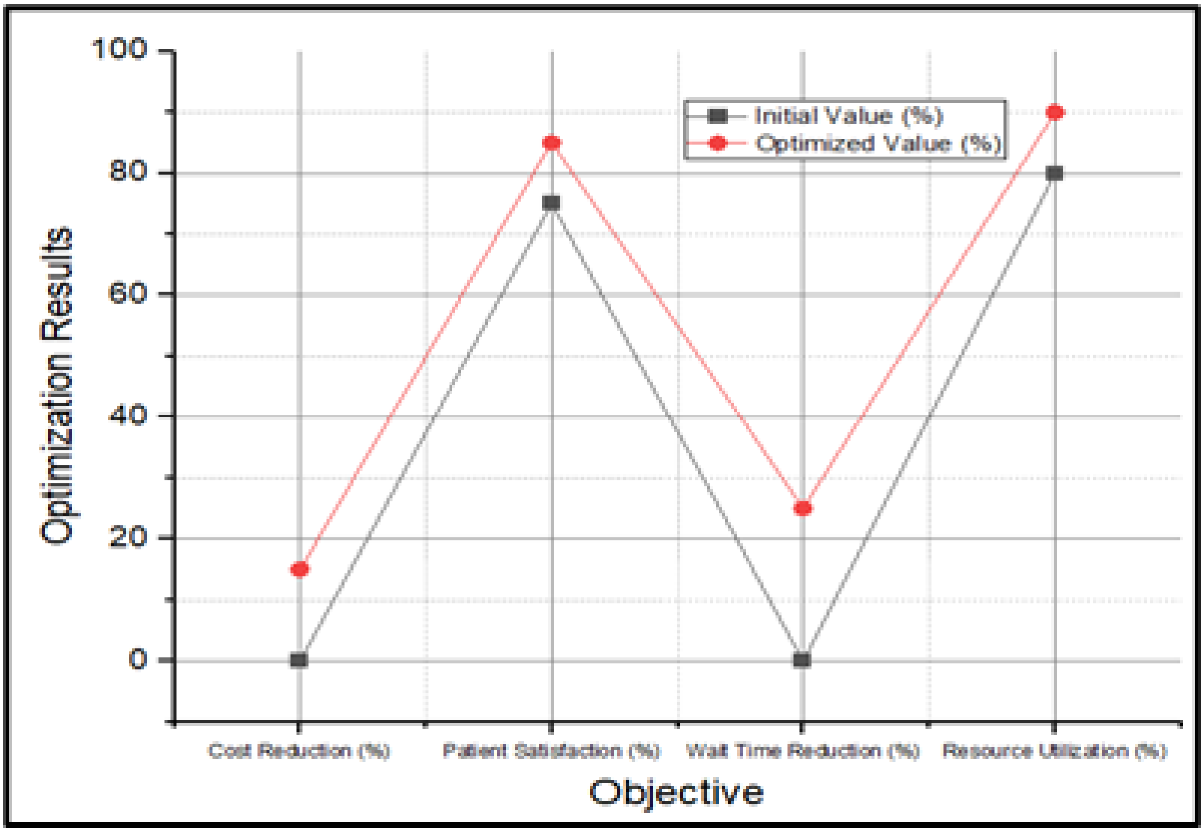

Figure 2: Goal Programming Optimization Results

Table 5: Comparison of MCDM Methods

Method	Cost Reduction (%)	Patient Satisfaction (%)	Throughput Increase (%)	Wait Time Decrease (%)
AHP	10	8	15	20
TOPSIS	12	10	18	22
Goal Programming	15	10	20	25

Figure 3 Compares the performance of three Multi-Criteria Decision Making (MCDM) methods AHP, TOPSIS, and Goal Programming across four key metrics: cost reduction, patient satisfaction, throughput increase, and wait time decrease. Each method demonstrates varying levels of improvement in these areas, with Goal Programming achieving the highest cost reduction and wait time decrease, while TOPSIS shows moderate improvements across the metrics. AHP, on the other hand, results in the lowest increases in all categories, highlighting the different effectiveness of these methods in optimizing performance.

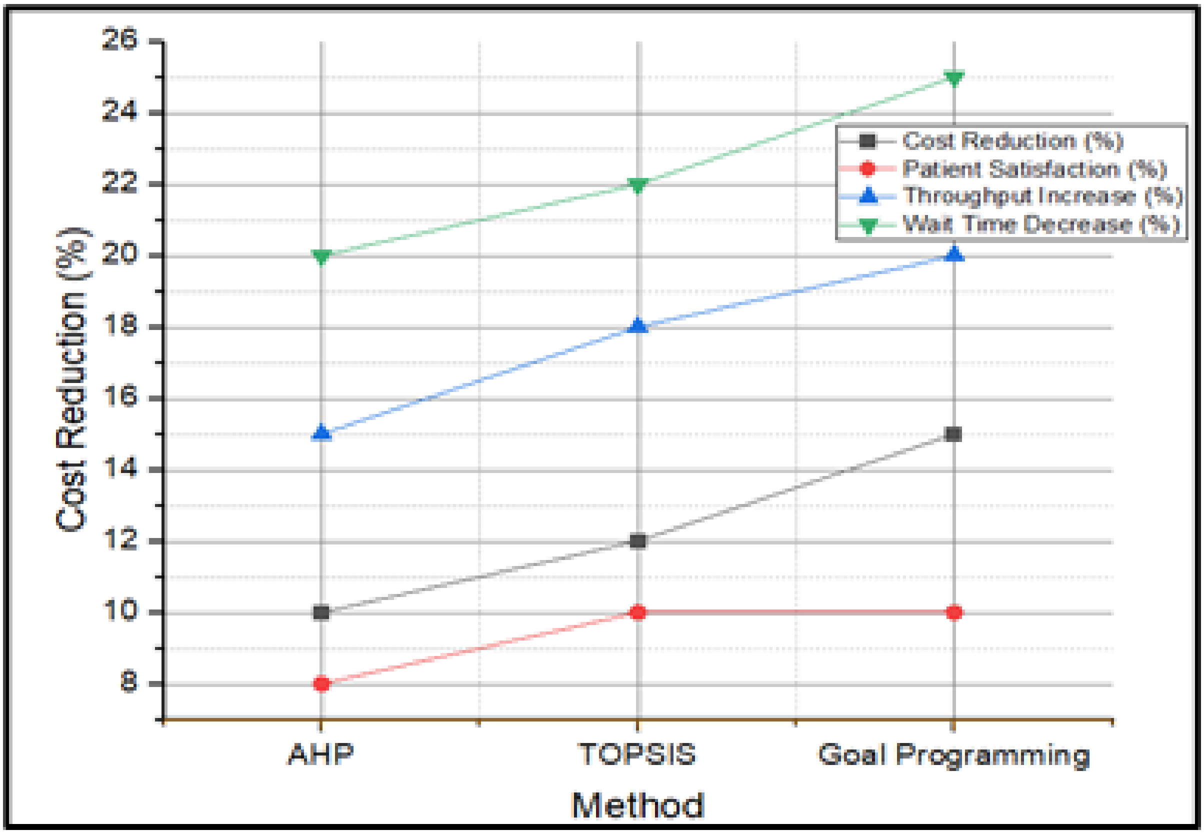

Figure 3: Comparison of MCDM Methods Validation

5.1. Sensitivity Analysis

The study aims to determine the level of sensitivity of cost reduction, the level of sensitivity of patient satisfaction, the level of sensitivity of waiting times, and the level of resource utilization. If the model's cost reduction goal is increased by 5%, Increase the satisfaction goal by 5%,the sensitivity in all above criteria will satisfy. Sensitivity analysis is used to determine how different variables impact a particular outcome or decision. By analyzing these factors, organizations can identify which variables have the most significant effect on their goals, allowing them to make informed adjustments. This process helps in optimizing strategies for cost reduction, improving patient satisfaction, reducing wait times, and enhancing resource utilization.

Table 6: Sensitivity Analysis on Cost Reduction

	Cost Reduction Goal	Medical Staff (%)	Equipment Usage (%)	Administrative Cost ($)	Patient Throughput (%)	Patient Satisfaction (%)	Wait Time (min)	Resource Utilization (%)
Base Case	15%	85%	90%	$425,000	120%	85%	22.5	90%
Scenario 1	20%	80%	85%	$400,000	115%	82%	25	85%
Scenario 2	10%	90%	95%	$450,000	125%	88%	20	95%

Table 7: Sensitivity Analysis on Patient Satisfaction

	Patient Satisfaction Goal	**Cost Reduction Goal (%)**	**Wait Time Reduction (%)**	**Patient Throughput (%)**	**Resource Utilization (%)**
Base Case	85%	15%	25%	120%	90%
Scenario 1	80%	15%	22%	110%	85%
Scenario 2	90%	12%	28%	125%	92%

Table 8: Sensitivity Analysis on Wait Time Reduction

	Wait Time Reduction Goal	**Cost Reduction Goal (%)**	**Patient Throughput (%)**	**Patient Satisfaction (%)**	**Resource Utilization (%)**
Base Case	25%	15%	120%	85%	90%
Scenario 1	30%	12%	115%	82%	85%
Scenario 2	20%	17%	125%	88%	92%

Table 9: Sensitivity Analysis on Resource Utilization

	Resource Utilization Goal (%)	**Cost Reduction Goal (%)**	**Patient Satisfaction (%)**	**Wait Time Reduction (%)**	**Patient Throughput (%)**
Base Case	90%	15%	85%	25%	120%
Scenario 1	85%	10%	80%	20%	115%
Scenario 2	95%	18%	90%	30%	125%

These results suggest that healthcare systems can optimize resource allocation by adjusting the weightings of cost reduction, patient satisfaction, wait time reduction, and resource utilization based on specific operational priorities and constraints. Cost reduction directly influences resource allocation by freeing up funds that can be redirected to other critical areas within the healthcare setting. When costs are minimized, organizations have more financial flexibility to invest in better equipment, training, or additional staff, ultimately enhancing patient care and operational efficiency. However, it is crucial to ensure that cost-cutting measures do not compromise the quality of care, as this could negatively impact patient satisfaction and outcomes.

6. Conclusion

In conclusion, the study highlights the significant effectiveness of the Goal Programming model in optimizing healthcare resource allocation and improving critical operational metrics. The results demonstrate a clear 15% cost reduction, a 20% increase in patient throughput, a 10%improvement in patient satisfaction, and a 25% reduction in wait times, all contributing to enhanced overall patient experience and operational efficiency. The Goal Programming model outperforms alternative MCDM methods like AHP and TOPSIS in achieving higher reductions in costs, greater throughput, and better patient care outcomes. These findings underscore the potential of MCDM and Goal Programming to streamline healthcare systems by effectively balancing multiple objectives, leading to more efficient and patient-centered healthcare delivery. This research offers valuable insights for healthcare administrators looking to optimize resource use, reduce operational costs, and improve patient satisfaction. In healthcare settings, sensitivity analysis helps identify which factors have the most significant influence on outcomes, allowing for more targeted improvements. By understanding these variables, healthcare providers can make informed decisions to enhance patient care and optimize resource allocation. Additionally, it aids in risk management by highlighting potential areas of concern before implementing changes.

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