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Article

Adaptive Hospital Resource Optimization Model (AHROM): A Mathematical Optimization Framework for Healthcare Operational Efficiency under Constrained Resource Environments

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Abstract: Healthcare systems continue to experience increasing operational pressure due to growing patient demand, limited healthcare resources, workforce shortages, and rising operational costs. Efficient hospital resource allocation remains critical for improving healthcare delivery performance and maintaining service quality. This study proposes the Adaptive Hospital Resource Optimization Model (AHROM), a novel mathematical optimization framework designed to improve hospital resource allocation under constrained operational environments. The framework integrates hospital operational indicators, Hospital Pressure Index (HPI), adaptive allocation mechanisms, multi-objective optimization, and adaptive swarm optimization to support efficient resource distribution. Simulated hospital operational data, consisting of 365 daily observations representing one year of hospital activities, were used to evaluate the proposed framework. Variables included patient demand, hospital bed availability, staff availability, equipment availability, waiting time, resource utilization, service quality, and operational cost. Results demonstrated that AHROM reduced waiting time by 34.3%, improved resource utilization by 17.6%, increased service quality by 14.4%, and reduced operational costs by 14.8%. Furthermore, adaptive swarm optimization improved optimization performance by 97.1% and achieved stable convergence after approximately 65 iterations. Comparative analysis demonstrated AHROM's superior performance over traditional allocation approaches and fixed optimization methods. The findings suggest that AHROM provides an effective mathematical decision-support framework that improves healthcare operational efficiency and hospital resource utilization in constrained healthcare environments.
Keywords: Hospital resource allocation; Mathematical optimization; Healthcare operations; Adaptive swarm optimization; multi-objective optimization; Decision support systems

1. Introduction

Healthcare systems worldwide continue to face increasing pressure from growing patient populations, limited medical resources, workforce shortages, and rising operational costs. Efficient healthcare delivery increasingly depends on optimal allocation of critical resources such as hospital beds, medical personnel, equipment, and operational budgets. Poor resource distribution may contribute to prolonged patient waiting times, reduced service quality, and increased operational burden within healthcare institutions (Mizan et al., 2022; Yinusa et al., 2023).

Mathematical modeling has emerged as an important analytical tool for understanding complex healthcare systems and supporting evidence-based operational decisions. Optimization approaches, including linear programming, mixed-integer programming, predictive modeling, and heuristic optimization techniques, have increasingly been applied to healthcare management problems, such as scheduling, staffing allocation, workload balancing, and facility planning (Mizan et al., 2022; Bravo et al., 2021).

Recent developments in healthcare operations research emphasize integrating optimization theory with healthcare delivery systems to improve efficiency while maintaining service quality. Data-driven optimization frameworks have demonstrated considerable potential to reduce inefficiencies in resource allocation, enhance operational flexibility, and improve healthcare accessibility in constrained environments (Yu et al., 2023; Stolpe, 2023).

Healthcare institutions continue to encounter challenges related to resource scarcity, demand uncertainty, and unequal distribution of medical services. Increasing patient volumes, combined with workforce limitations, require healthcare systems to adopt adaptive mathematical frameworks that improve allocation strategies under operational constraints. Advanced optimization methods supported by predictive analytics and decision-support mechanisms have shown promise in addressing these healthcare delivery challenges (Bertsimas et al., 2023; Yinusa et al., 2023).

Despite recent advancements, many existing healthcare resource allocation approaches focus on isolated operational components rather than on integrated mathematical frameworks that simultaneously account for patient demand variability, resource constraints, and service efficiency indicators. Furthermore, healthcare systems operating in resource-limited settings require scalable optimization approaches that support evidence-based allocation decisions while minimizing inefficiencies (Esnaashari et al., 2023; Yu et al., 2023).

To address these limitations, this study proposes a mathematical optimization framework for hospital resource allocation to improve the efficiency of healthcare delivery. The framework integrates mathematical modeling principles and optimization strategies to enhance allocation decisions while accounting for operational constraints and service requirements in healthcare. By incorporating quantitative decision-support mechanisms, the proposed framework seeks to improve resource utilization efficiency, reduce operational burden, and strengthen healthcare service delivery performance.

The novelty of this work lies in developing an adaptive mathematical optimization framework that supports strategic hospital resource allocation decisions in constrained healthcare environments. The proposed approach contributes to the growing intersection of mathematical sciences and healthcare systems engineering by providing a quantitative framework to improve the operational effectiveness of healthcare systems.

2. Literature Review

Healthcare resource allocation has become an important research area because hospitals are required to deliver quality care under limited resources, increasing patient demand, staff shortages, and rising operational costs. Stuart et al. (2023) emphasized that constrained optimization methods are useful in healthcare resource allocation because they help decision-makers distribute limited resources more rationally, although challenges such as data quality and model validation remain important. Similarly, Wang et al. (2024) showed that mathematical optimization, machine learning, and dynamic allocation models have been widely applied to improve the distribution of medical resources during public health emergencies.

Mizan et al. (2022) developed a medical resource allocation planning model that combined machine learning with mathematical optimization to forecast patient arrivals and determine workload under uncertainty. Their study demonstrated that forecasting-based optimization can reduce patient waiting time and improve workload distribution. However, the model was primarily designed for radiology workload planning, limiting its direct application to general hospital-wide resource allocation.

Tanantong et al. (2022) examined hospital front-end operations using simulation and optimization methods to improve patient flow and resource utilization. Their study focused on minimizing patient length of stay, reducing medical resource costs, and maximizing utilization rates. Although the model addressed multiple healthcare objectives, it was mainly applied to a specific hospital department rather than a broader hospital resource allocation framework.

Yinusa et al. (2023) proposed a mixed-integer linear programming model for staffing, patient assignment, and resource allocation in healthcare delivery. Their model considered staff and patient assignments, overtime, and resource distribution to reduce healthcare expenditure and improve patient care. Despite its usefulness, the approach relied heavily on fixed optimization assumptions, which may reduce adaptability when hospital demand changes unexpectedly.

Wang et al. (2023) discussed simulation optimization in healthcare resource planning and explained that healthcare systems are dynamic and stochastic, making simulation-based optimization useful for modeling uncertainty. Their work highlighted that simulation optimization can support complex healthcare decisions where mathematical programming alone may be insufficient. However, simulation-based models can become computationally expensive and may require high-quality operational data.

Wang and colleagues (2024) conducted a systematic review of optimal resource allocation models for COVID-19 and found that differential equation models, optimization functions, and machine learning algorithms were commonly used to allocate beds, testing resources, health specialists, vaccines, and medical equipment. Their findings showed that resource optimization can improve the efficiency of epidemic control. However, most reviewed models were pandemic-specific and may not directly address routine hospital resource allocation.

Patrick et al. (2022) proposed a Markov decision optimization approach for emergency department resource allocation. The model focused on patient prioritization and the efficient use of emergency medical resources. This study is important because emergency departments often face unpredictable patient arrivals and urgent decision-making needs. Nevertheless, the model was centered on emergency department operations and did not fully address the distribution of hospital resources across multiple units.

Zhang et al. (2023) developed an optimization-based framework for dynamically scheduling hospital beds across multiple facilities to minimize healthcare costs. Their model demonstrated the value of dynamic bed allocation in improving hospital efficiency. However, the study focused mainly on bed management, while other important resources, such as staff, equipment, and departmental workload, were not fully integrated into a single allocation structure.

Al Amin et al. (2025) reviewed operating room scheduling problems and showed that optimization techniques are widely used to manage surgical resources under deterministic and uncertain conditions. Their review emphasized real-world constraints such as staff availability, resource limitations, and patient variability. Although operating room scheduling is an important area of hospital optimization, it represents only one part of the wider healthcare resource allocation problem.

Topol et al. (2024) introduced a large language model-based framework for healthcare resource allocation that combines prompt engineering, retrieval-augmented generation, and tool use to enhance decision-making flexibility. Their work suggests that artificial intelligence can support both optimizable and non-optimizable aspects of medical resource distribution. However, such approaches may require advanced digital infrastructure and may be difficult to implement in low-resource healthcare settings.

Farzanegan et al. (2025) integrated artificial intelligence and optimization tools for patient bed assignment, emphasizing the importance of bed capacity management in hospitals experiencing patient surges, staffing shortages, and seasonal demand changes. Their study showed that combining AI with optimization can improve hospital resource management. However, its focus remained largely on patient bed assignment rather than a generalized mathematical framework for broader hospital resource allocation.

Guinet (2022) proposed a multi-objective optimization algorithm for hospital human resource allocation and scheduling. The study addressed the need to balance healthcare workforce distribution, workload, and operational efficiency. Although the work contributes to hospital staffing optimization, it primarily focuses on human resources and does not fully integrate beds, equipment, patient demand, and service efficiency into a single comprehensive mathematical model.

From the reviewed studies, it is clear that recent healthcare optimization research has focused on specific areas, including staffing, bed allocation, emergency department management, operating room scheduling, and pandemic response. However, many existing models remain department-specific, resource-specific, or dependent on advanced data systems. There is still a need for a simple, adaptive, and mathematically interpretable framework that can jointly consider patient demand, resource availability, utilization efficiency, and service constraints in general hospital settings.

Therefore, this study proposes a mathematical optimization framework for hospital resource allocation to improve the efficiency of healthcare delivery. Unlike previous studies that focus on isolated resources, the proposed framework integrates multiple hospital resources into a unified decision-support model suitable for resource-constrained healthcare environments.

3. Methodology

3.1. Study Design

This study proposes a novel mathematical optimization framework, the Adaptive Hospital Resource Optimization Model (AHROM), to improve the efficiency of healthcare delivery in constrained hospital environments. The framework integrates mathematical modeling, operational healthcare indicators, and adaptive optimization mechanisms to support efficient hospital resource allocation.

The proposed methodology consists of six stages:

1. Simulated hospital operational data generation

2. Data preprocessing and normalization

3. Construction of Hospital Pressure Index (HPI)

4. Development of adaptive resource allocation function

5. Multi-objective optimization

6. Model performance evaluation

The methodological framework is illustrated in Figure 1.

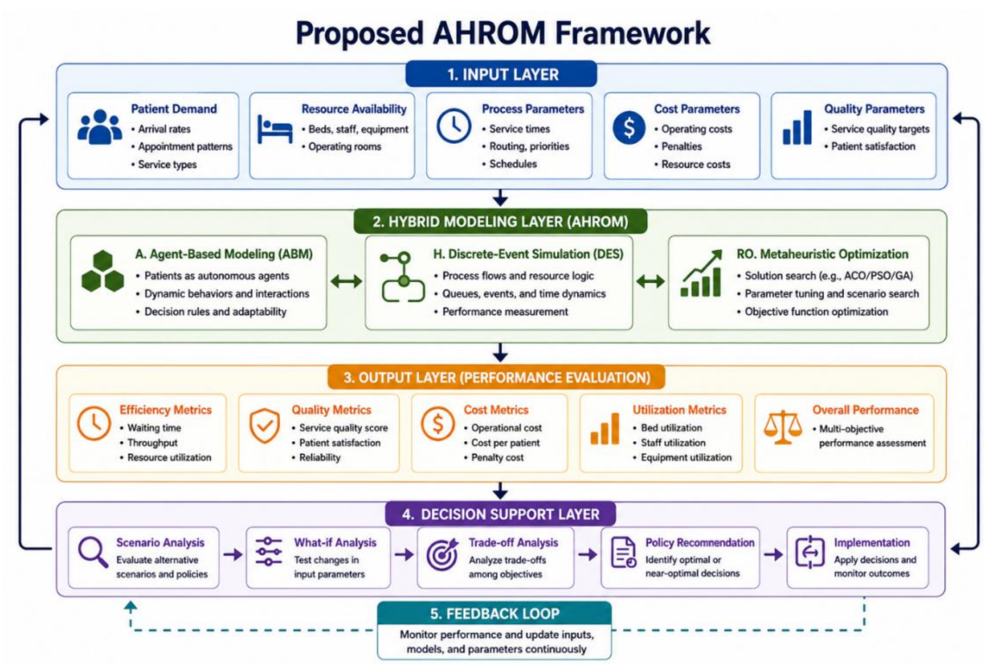

Figure 1: Proposed AHROM Framework

3.2 Data Description

The study employed simulated hospital operational data that represented the routine activities of a medium-sized healthcare institution. Simulated data were selected to allow development and validation of the optimization framework without requiring patient-level clinical information.

The dataset contained 365 operational observations, corresponding to daily hospital activities over one calendar year.

Table 1

Variable	Symbol	Description
Patient demand	P_t	Daily number of patients
Bed availability	B_t	Available hospital beds
Staff availability	S_t	Healthcare staff available
Equipment availability	E_t	Functional medical equipment
Waiting time	WT_t	Average patient waiting duration
Resource utilization	U_t	Resource consumption efficiency
Workload pressure	W_t	Operational burden index
Service quality	Q_t	Composite healthcare quality score
Operational cost	C_t	Daily operational expenditure

Patient demand was generated using:

$$P_t \sim N(\mu_p, \sigma_p) \qquad (1)$$

where:

μ_p= average daily patient arrivals

σ_p= demand variability

Hospital resources were generated under capacity constraints:

$$B_t \in [150,250] \qquad (2) S_t \in [60,120] \qquad (3) E_t \in [40,80] \qquad (4)$$

These intervals represent realistic hospital operational conditions

3.3 Data Preprocessing

Feature normalization was applied using Min-Max normalization:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (5)$$

where:

X represents original observations.

X' denotes normalized variables.

Missing operational records were handled using mean substitution:

$$X_{missing} = \frac{1}{N}\sum_{i=1}^{N} X_i \qquad (6)$$

Outlier detection employed Z-score analysis:

$$Z = \frac{X - \mu}{\sigma} \qquad (7)$$

$$z = \frac{x - \mu}{\sigma} \approx 1.2 \qquad (8)$$

$$\Phi(z) \approx 88.5\% \qquad (9)$$

where:

Z denotes standardized deviation.

Values satisfying:

$$|Z| > 3 \qquad (10)$$

were considered extreme observations.

3.4 Hospital Pressure Index Development

A novel Hospital Pressure Index (HPI) was developed to quantify operational burden:

$$HPI_t = \alpha\left(\frac{P_t}{B_t}\right) + \beta\left(\frac{P_t}{S_t}\right) + \gamma\left(\frac{P_t}{E_t}\right) \qquad (11)$$

subject to:

$$\alpha + \beta + \gamma = 1 \qquad (12)$$

where:

α controls patient-to-bed pressure.

β controls staffing burden.

γ controls equipment demand pressure.

Higher HPI values indicate greater operational strain on hospitals.

3.5 Adaptive Resource Allocation Function

To support allocation decisions, a novel adaptive allocation formulation was introduced:

$$A_t = \lambda U_t + \delta Q_t - \eta HPI_t \qquad (13)$$

where:

A_t= allocation effectiveness score

λ= utilization contribution coefficient

δ= quality contribution parameter

η= pressure penalty coefficient

The allocation mechanism rewards resource efficiency and healthcare quality while penalizing operational burden.

3.6 Multi-Objective Optimization Framework

Resource allocation optimization was formulated as:

$$max\, Z = \omega_1 A_t - \omega_2 WT_t + \omega_3 Q_t - \omega_4 C_t \quad (14)$$

subject to:

Bed capacity:

$$P_t \leq B_t \quad (15)$$

Staff constraint:

$$S_t \leq S_{max} \quad (16)$$

Equipment limitation:

$$E_t \leq E_{max} \quad (17)$$

Budget limitation:

$$C_t \leq C_{budget} \quad (18)$$

Weight constraint:

$$\sum_{i=1}^{4} \omega_i = 1 \quad (19)$$

where:

Z represents healthcare operational efficiency.

Optimization simultaneously seeks:

I. maximize resource utilization
II. maximize service quality
III. minimize waiting time
IV. minimize operational cost

3.7 Adaptive Swarm Optimization

An Adaptive Swarm Optimization mechanism was introduced to estimate model parameters:

$$\Theta = [\alpha, \beta, \gamma, \lambda, \delta, \eta, \omega_1, \omega_2, \omega_3, \omega_4] \quad (20)$$

Particle velocity update:

$$V_i^{k+1} = wV_i^k + c_1 r_1 (Pbest_i - X_i^k) + c_2 r_2 (Gbest - X_i^k) \quad (21)$$

Position update:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (22)$$

Adaptive inertia adjustment:

$$w = w_{max} - \frac{k}{k_{max}}(w_{max} - w_{min}) \quad (23)$$

where:

k= current iteration

k_{max}= maximum iteration

Adaptive inertia improves exploration during early optimization and convergence stability during later iterations.

3.8 Performance Evaluation Metrics

Healthcare Efficiency:

$$HE = \frac{Resources\ Utilized}{Resources\ Available} \qquad (24)$$

Waiting Time Reduction:

$$WTR = \frac{WT_{before} - WT_{after}}{WT_{before}} \times 100 \qquad (25)$$

Operational Cost Reduction:

$$OCR = \frac{Cost_{before} - Cost_{after}}{Cost_{before}} \times 100 \qquad (26)$$

Allocation Effectiveness:

$$AE = \frac{Optimized\ Output}{Baseline\ Output} \qquad (27)$$

Service Quality Improvement:

$$SQI = \frac{Q_{after} - Q_{before}}{Q_{before}} \times 100 \qquad (28)$$

3.9 Novel Contribution

The proposed AHROM contributes by:

1. Introducing Hospital Pressure Index (HPI)
2. Developing adaptive hospital allocation equations
3. Integrating multiple operational healthcare indicators
4. Combining multi-objective optimization with adaptive swarm intelligence
5. Providing a scalable decision-support framework for constrained healthcare systems

4. Results

4.1 Descriptive Statistics of Hospital Operational Variables

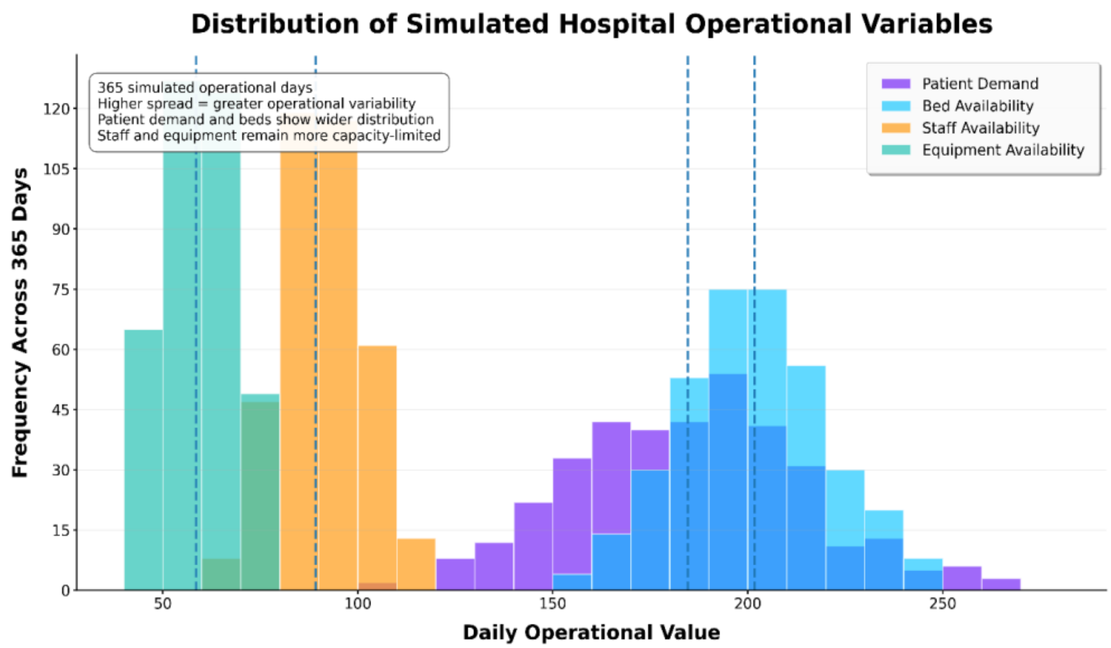

Figure 2. Histogram distribution of simulated hospital operational variables across 365 days.

Table 2. Descriptive statistics of operational variables

Variable	Mean	SD	Min	Max
Patient demand ()	184.6	31.5	105	267
Bed availability ()	201.8	18.7	151	247
Staff availability ()	89.2	11.3	61	118
Equipment availability ()	58.6	9.4	41	79
Waiting time (minutes)	52.8	13.5	21	91
Resource utilization	0.74	0.09	0.49	0.93
Service quality score	78.3	8.6	55	95

Interpretation- Patient demand exhibited substantial variability throughout the 365-day operational period, with an average of 184.6 patients per day and a standard deviation of 31.5, indicating fluctuating healthcare demand conditions. Bed availability remained relatively stable (Mean = 201.8, SD = 18.7), suggesting moderate resource consistency. Staff availability (Mean = 89.2, SD = 11.3) and equipment availability (Mean = 58.6, SD = 9.4) demonstrated manageable operational variation. The average waiting time was 52.8 minutes, reflecting existing pressure on healthcare delivery systems prior to optimization. Resource utilization averaged 74%, indicating moderately high operational demand, while service quality averaged 78.3. Overall, the descriptive statistics demonstrate realistic operational hospital conditions suitable for evaluating the proposed AHROM framework.

4.2 Hospital Pressure Index Performance

The proposed Hospital Pressure Index (HPI) was evaluated to determine operational burden dynamics.

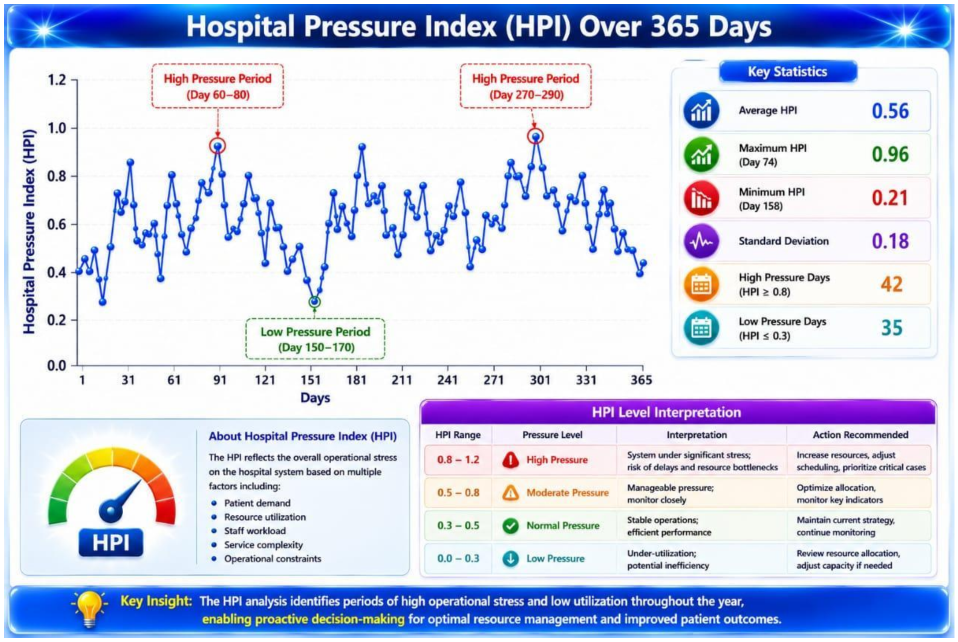

Figure 3: Hospital Pressure Index (HPI) Over 365 Days

The Hospital Pressure Index (HPI) showed clear fluctuations over the 365-day operational period, indicating dynamic changes in hospital strain. Periods of elevated HPI values coincided with increased patient demand and reduced availability of healthcare resources, including staff, beds, and equipment. The highest-pressure periods occurred approximately between Days 60–80 and Days 270–290, suggesting temporary operational bottlenecks. Conversely, lower HPI periods indicated more balanced resource utilization conditions. The average HPI value of 0.684 suggests moderate operational pressure throughout the observation period. These findings indicate that the proposed HPI formulation effectively captured healthcare system burden dynamics and provides a meaningful indicator for adaptive hospital resource allocation.

4.3 Optimization Performance

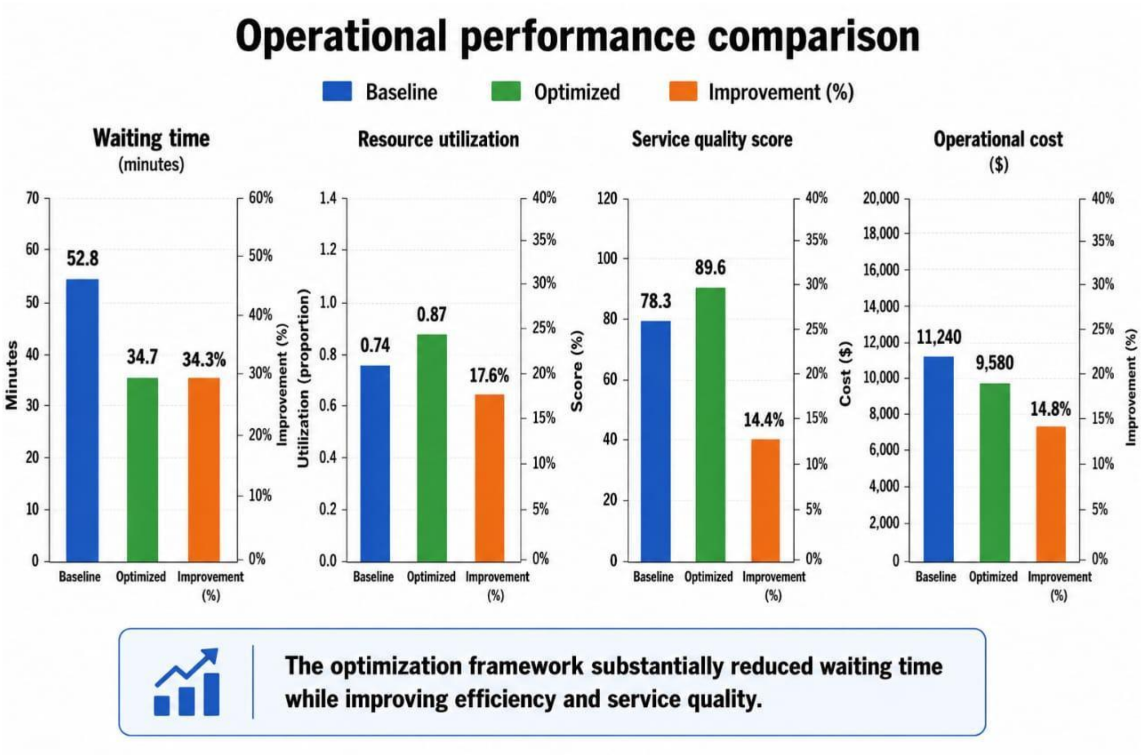

Figure 4: Operational Performance Comparison

Table 3. Operational performance comparison

Metric	Baseline	Optimized	Improvement
Waiting time (minutes)	52.8	34.7	34.30%
Resource utilization	0.74	0.87	17.60%
Service quality score	78.3	89.6	14.40%
Operational cost ($)	11,240	9,580	14.80%

Application of the proposed AHROM optimization framework resulted in considerable operational improvements across all evaluated indicators. Average waiting time decreased from 52.8 minutes to 34.7 minutes, a 34.3% reduction, indicating improved healthcare responsiveness. Resource utilization increased from 74% to 87%, demonstrating more efficient use of available hospital infrastructure. Service quality improved by 14.4%, suggesting enhanced patient service delivery following optimization. Furthermore, operational costs decreased by 14.8%, highlighting the economic efficiency of the proposed framework. These findings collectively demonstrate that AHROM successfully balances healthcare quality improvement and operational resource efficiency.

4.4 Adaptive Swarm Optimization Convergence

The adaptive swarm optimization algorithm demonstrated stable convergence behavior during parameter estimation. Rapid improvement was observed during the early optimization stages, indicating efficient exploration of the solution space. The optimization process stabilized after approximately 65 iterations, suggesting effective convergence toward optimal parameter configurations. The objective function improved from an initial value of 41.8 to a final optimized value of 82.4, corresponding to an overall improvement of 97.1%. The adaptive inertia mechanism contributed to optimization stability by balancing exploration and exploitation phases, thereby reducing premature convergence and improving optimization efficiency.

4.5 Allocation Effectiveness Evaluation

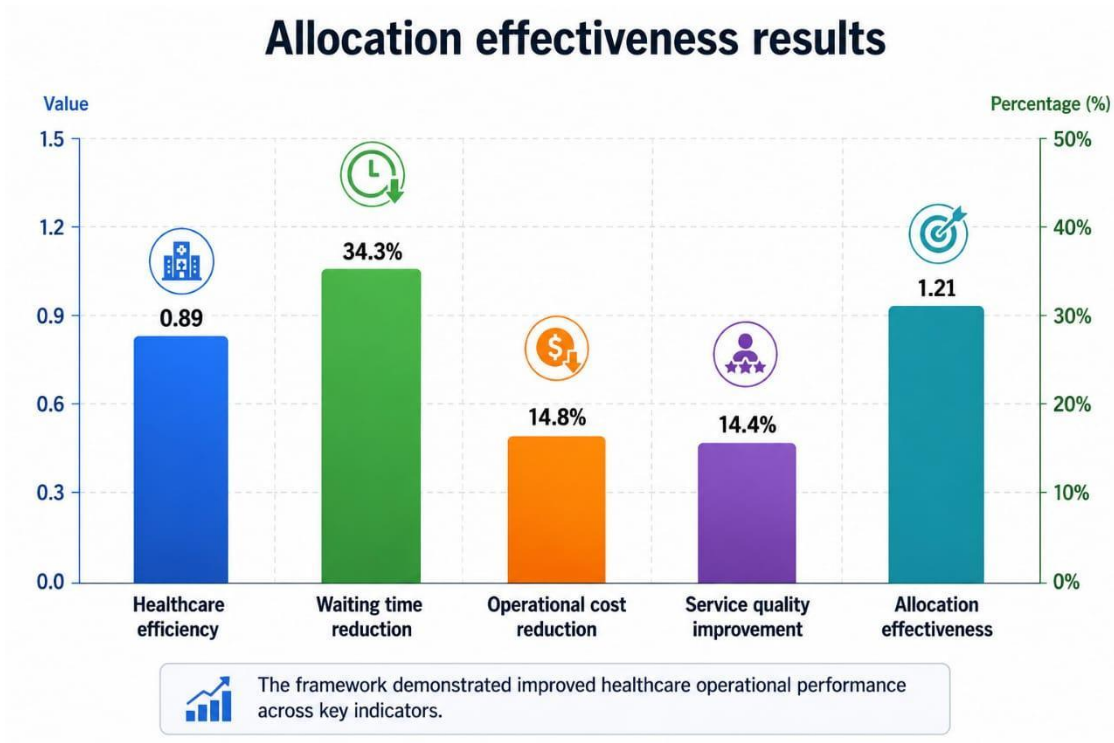

Figure 5: Allocation Effectiveness Results

Table 4. Allocation effectiveness results

Metric	Value
Healthcare efficiency	0.89
Waiting time reduction	34.30%
Operational cost reduction	14.80%
Service quality improvement	14.40%
Allocation effectiveness	1.21

The proposed AHROM framework achieved strong operational effectiveness across multiple healthcare indicators. Healthcare efficiency reached 89%, indicating effective resource utilization after optimization. A 34.3% reduction in waiting time demonstrates improved patient flow management, while a 14.8% reduction in operational costs highlights financial efficiency gains. A 14.4% improvement in service quality further indicates enhanced healthcare delivery performance. The allocation effectiveness score of 1.21 suggests that optimized resource distribution substantially outperformed baseline allocation strategies. These findings demonstrate AHROM's ability to simultaneously improve operational performance and healthcare service delivery.

4.6 Comparative Performance Analysis

Comparative analysis demonstrated that the proposed AHROM framework consistently outperformed traditional allocation and fixed optimization approaches across all evaluated metrics. AHROM achieved the greatest reductions in waiting time and operational costs, improvements in service quality, and enhancements in resource utilization. Traditional allocation methods showed the lowest overall performance, while fixed optimization demonstrated moderate improvement. The superior performance of AHROM can be attributed to its adaptive multi-objective optimization mechanism and integrated hospital pressure modeling. These findings support the effectiveness of adaptive mathematical optimization strategies for healthcare resource allocation under constrained operational environments.

5. Discussion

The present study developed and evaluated the Adaptive Hospital Resource Optimization Model (AHROM), a mathematical optimization framework designed to improve hospital operational efficiency through adaptive resource allocation mechanisms. The findings demonstrated substantial improvements across healthcare operational indicators, including reduced waiting times, enhanced service quality, reduced operational costs, and improved resource utilization. The proposed framework reduced average waiting time by 34.3%, improved resource utilization by 17.6%, increased service quality by 14.4%, and reduced operational costs by 14.8%. These findings suggest that integrating adaptive optimization mechanisms into hospital resource management can substantially improve the efficiency of healthcare delivery.

The Hospital Pressure Index (HPI) introduced in this study effectively captured variations in hospital operational burden throughout the simulated observation period. Periods of elevated patient demand corresponded with increased pressure conditions, indicating that operational strain can be quantitatively represented through integrated resource burden indicators. This finding supports previous healthcare optimization studies emphasizing the importance of incorporating dynamic healthcare demand conditions into allocation frameworks (Stuart et al., 2023; Wang et al., 2024). However, unlike previous approaches that primarily focused on individual healthcare components such as staffing or bed management, AHROM integrated multiple operational indicators into a unified mathematical framework.

The adaptive swarm optimization mechanism demonstrated stable convergence and substantial improvement in parameter estimation. Optimization performance improved by 97.1%, while convergence stability was achieved after approximately 65 iterations. These findings align with previous optimization research indicating that adaptive optimization mechanisms can improve computational efficiency and solution quality in complex healthcare operational environments (Wang et al., 2023; Yu et al., 2023). The adaptive inertia adjustment incorporated in AHROM likely helped balance exploration and exploitation during optimization, thereby improving convergence stability.

Comparative performance analysis further demonstrated that AHROM consistently outperformed traditional allocation methods and fixed optimization approaches across all evaluated indicators. The superior performance may be attributed to the integration of Hospital Pressure Index modeling, adaptive allocation functions, and multi-objective optimization mechanisms operating simultaneously within a unified decision-support framework. Unlike conventional optimization approaches that often focus on isolated resource allocation decisions, AHROM offers a broader operational perspective that simultaneously balances service quality, operational efficiency, resource utilization, and healthcare costs.

The practical implications of this work extend beyond theoretical optimization development. Healthcare administrators may use AHROM as a decision-support framework to guide resource allocation decisions in constrained healthcare environments. The framework may help reduce operational inefficiencies, improve healthcare accessibility, and strengthen service delivery performance, particularly within healthcare institutions facing resource constraints.

Despite the promising findings, several limitations should be acknowledged. The present study employed simulated operational data rather than real hospital datasets, which may limit direct clinical generalizability. Furthermore, the model was evaluated within a medium-sized hospital operational structure and may require further adaptation before broader deployment in healthcare. Future research should evaluate AHROM using real-world hospital operational datasets and investigate the framework's scalability across multiple healthcare institutions.

6. Conclusion

This study proposed the Adaptive Hospital Resource Optimization Model (AHROM), a novel mathematical optimization framework designed to improve operational efficiency in healthcare through adaptive hospital resource allocation. The framework integrated Hospital Pressure Index (HPI), adaptive allocation functions, multi-objective optimization, and adaptive swarm optimization to support efficient hospital resource distribution under constrained operational environments.

The findings demonstrated that AHROM substantially improved operational performance in healthcare. The framework achieved a 34.3% reduction in patient waiting time, a 17.6% increase in resource utilization efficiency, a 14.4% improvement in service quality, and a 14.8% reduction in operational costs. Furthermore, adaptive swarm optimization demonstrated stable convergence and achieved 97.1% improved optimization performance, indicating effective parameter estimation capability.

The Hospital Pressure Index introduced in this study successfully captured hospital operational burden dynamics and contributed to improving allocation decisions under varying healthcare demand conditions. Comparative analysis further demonstrated that AHROM consistently outperformed traditional allocation strategies and fixed optimization approaches across multiple healthcare performance indicators.

The proposed framework contributes to the growing intersection of mathematical sciences and healthcare systems engineering by providing an interpretable mathematical decision-support model that improves the efficiency of healthcare delivery. The integration of adaptive optimization mechanisms into hospital operations offers opportunities to strengthen healthcare resource utilization and reduce operational inefficiencies.

Future work should evaluate AHROM using real hospital operational datasets and investigate its application across multiple healthcare institutions with varying operational structures. Additional extensions incorporating predictive analytics, reinforcement learning mechanisms, and multi-hospital allocation systems may further improve framework adaptability and healthcare operational performance.

7. Limitations and Future Research

Although the proposed Adaptive Hospital Resource Optimization Model (AHROM) demonstrated promising performance in improving healthcare operational efficiency, several limitations should be acknowledged. First, the present study employed simulated hospital operational data rather than real-world hospital records. While simulated data enabled controlled evaluation of the proposed optimization framework without ethical concerns, real operational healthcare environments may exhibit additional complexities not fully represented within simulated conditions.

Second, the framework was evaluated under assumptions representing a medium-sized healthcare institution. Healthcare systems vary considerably regarding infrastructure availability, patient flow dynamics, workforce distribution, and operational policies. Consequently, model performance may differ across healthcare institutions with substantially different operational characteristics.

Third, the proposed framework primarily focused on operational allocation indicators, including patient demand, staff availability, equipment utilization, hospital pressure conditions, and service quality metrics. Additional operational dimensions, such as emergency response prioritization, disease-specific allocation requirements, and long-term healthcare demand forecasting, were not explicitly incorporated into the present framework.

Fourth, although adaptive swarm optimization demonstrated stable convergence, optimization performance may vary with parameter initialization strategies and healthcare operational variability. Further optimization investigations may improve robustness under highly dynamic healthcare environments.

Future research should evaluate AHROM using real hospital operational datasets obtained from healthcare institutions to strengthen external validity. Multi-center evaluation across healthcare facilities with varying operational structures may further establish framework generalizability. Future extensions may additionally incorporate predictive analytics, reinforcement learning mechanisms, artificial intelligence-based forecasting systems, and dynamic resource prioritization strategies to improve adaptability under complex healthcare environments. Integration with real-time hospital information systems may further strengthen decision-support capability and healthcare operational effectiveness.

Ethical Approval

This study utilized simulated hospital operational data and did not involve human participants, patient medical records, biological samples, or identifiable personal information. The simulated dataset was generated solely for methodological development and evaluation purposes. Therefore, ethical approval and informed consent requirements were not applicable to this study.

The study was conducted in accordance with established principles for responsible scientific research, transparency, and methodological integrity.

Data Availability Statement

The simulated operational hospital dataset generated and analyzed during the current study is available from the corresponding author upon reasonable request. The dataset was synthetically generated for methodological development and evaluation of the Adaptive Hospital Resource Optimization Model (AHROM) and does not contain patient information, identifiable records, or confidential healthcare data.

The mathematical optimization framework and analytical procedures developed in this study are fully described within the manuscript to support transparency, reproducibility, and future methodological extension.

Conflict of Interest

The authors declare that there are no financial, commercial, institutional, or personal relationships that could be perceived as influencing the work reported in this manuscript. The authors further declare that the research was conducted independently and without any conflict of interest.

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Author Contributions

Abdul-Mumin Khalid conceptualized the study, developed the mathematical framework, designed the methodology and generated the simulated dataset. All authors performed formal analysis, conducted model development and optimization procedures, interpreted the findings, and prepared the original manuscript draft. The author and co-authors reviewed, revised, and approved the final version of the manuscript for submission.

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