Medical and Life Sciences (2026) 5(2): 1–18
ISSN (E): 2976-7245

Data-Driven Approaches to Healthcare Resource Optimization

Waleed Arshad[1]
Muneeb Arshad[2]
Maheen Arshad[3]
Muhammad Asjad Khan[4]*
Matiullah Khan[4]
Fizza Shahid[5]
Sara Aslam[6]
Arooba[7]

How to cite this article:
Arshad, W., Arshad, M., Arshad, M., Khan, M. A., Khan, M., Shahid, F., Aslam, S., & Arooba. (2026). *Data-driven approaches to healthcare resource optimization*. *Medical and Life Sciences, 5*(2), 1–18.

Received: 05 April 2026 / Accepted: 15 July 2026/ Published online: 01 August 2026

Abstract

Resource optimization in healthcare has emerged as a critical strategy to balance rising global healthcare demands with constrained financial, infrastructure, and human resources. This review synthesizes recent advances, challenges, and opportunities in optimizing healthcare delivery through data-driven allocation, scheduling, and workload management. Historical milestones reveal a trajectory from early applications of research in clinical logistics to the integration of explainable Artificial Intelligence (AI) and predictive platforms in modern systems. Foundational pillars of optimization, such as resource allocation, workload balance, and scheduling, are shown to directly impact patient wait times, staff burnout, and cost efficiency. The review highlights the transformative role of AI, Machine learning (ML), and operations research (OR) in predictive modeling, real-time decision support, and dynamic scheduling. Case studies demonstrate the success of AI-powered hospital bed forecasting, ML-driven surgical scheduling, and predictive staffing models in improving patient flow, reducing variability, and enhancing responsiveness during crises. Likewise, the integration of the Internet of Things (IoT), cloud, fog, and edge computing has enabled real-time monitoring and rapid decision-making in critical care. Spatial optimization models, including maximal coverage and P-median approaches, are further examined in their role in ensuring equitable healthcare access, particularly in underserved and rural regions. Despite these achievements, significant challenges persist. Data fragmentation, algorithmic bias, resistance to organizational change, and regulatory complexities hinder large-scale implementation. Solutions proposed include ontology–based interoperability frameworks,

[1]University of Surrey, Guildford, United Kingdom
[2]Service Institute of Medical Sciences, Lahore, Pakistan
[3]Rasheed Latif Medical College, Lahore, Pakistan
[4]Department of Biological Sciences, Faculty of Science and Technology, Virtual University of Pakistan, Raiwind Road Campus, Lahore, Pakistan
Corresponding Author: asjad.khan@vu.edu.pk
[5]Allied Burn and Reconstructive Surgery Centre, Allied Hospital, Faisalabad, Pakistan
[6]Akhtar Saeed Medical and Dental College, Lahore, Pakistan
[7]Department of Microbiology, Doctors Hospital and Medical Center, Lahore, Pakistan

Blockchain-enabled data governance, fairness-aware algorithms, and structured change management models. Emerging trends highlight the increasing importance of equity-driven spatial optimization, hybrid AI-GIS approaches, and collaborative governance to reduce disparities and enhance resilience. This review concludes that resource optimization in healthcare is no longer an ethical option but a strategic imperative. By harnessing predictive analytics, advanced optimization algorithms, and equity-centered frameworks, healthcare systems can achieve efficiency, resilience, and fairness. However, realizing these benefits requires a multidisciplinary approach that integrates technological innovation, policy alignment, and stakeholder engagement. The future of healthcare resource management lies in scalable, explainable, and equitable solutions capable of adapting to dynamic global health challenges.

Keywords: Healthcare resource optimization, Artificial Intelligence (AI), Machine Learning (ML), Operations Research (OR), Predictive Modeling, Spatial Optimization, Equity in healthcare, Healthcare Resilience

1 Introduction

Resource optimization in healthcare refers to the strategic planning and data-driven allocation, utilization, and scheduling of limited resources such as equipment, beds, staff, and hospital supplies to maximize the quality of treatment, operational efficiency, cost-effectiveness, and patient outcomes. It's a technical and moral imperative in systems where demand often exceed the capacity and supply chain of the system. Resource optimization helps balance clinical priorities, logistical realities, and financial constraints in real-time (Pardede et al., 2019). A comprehensive review of 190 case studies reveals how resource optimization in healthcare minimizes futile and burnout among healthcare workers by scheduling patients to ensure timely treatment, reduces waiting hours, and stress among patients. This study also highlights the pivotal role of healthcare scheduling in covering patient admissions, operating room logistics, and nurse shifts (Abdalkareem et al., 2021). Likewise, another study emphasizes the transformative role of data analytics and machine learning in the resource management of the healthcare sector by leveraging predictive modeling through AI (Artificial Intelligence) and real-time analysis of the data, forecasting patient inflows, and allocating the beds dynamically, optimizing inventory and staff deployment according to the need. It enhances the quality of the care, improves responsiveness during crises, as well as reduces the operational costs (Pushadapu, 2020). The importance of resource optimization becomes more pronounced and necessary in rural and underserved areas, where scarcity in the healthcare sector is common. In such areas, any decision of either allocating resources (Ventilators, beds, oxygen cylinders) or assigning shifts of nursing staff can be a matter of life and death. So in such settings importance of resource optimization is increasing for the need of optimization tools to help administration make these decisions with clarity and confidence, guided by evidence rather than intuition (Abdalkareem et al., 2021). Moreover, the researcher developed a mixed linear programming model to optimize staffing, resource allocation, and patient assignment. This model demonstrates how mathematical rigor can translate into real-world impact, reducing expenditures while improving care delivery (Yinusa & Faezipour, 2023). However, despite resource allocation's importance in the healthcare sector also experiences significant challenges under modern healthcare systems that are under immense and growing pressure. This convergence of rising demand from average demand, constrained resources, escalating costs, and unrelenting expectations for quality care has created a complex landscape that demands both resilience and innovation (Abdalkareem et al., 2021). Healthcare demands are surging globally due to chronic disease prevalence, an aging population, and more access to medical technologies. A researcher explained that in the COVID-19 pandemic, the demand overwhelmed the well-established healthcare systems and forced rapid adaptations across clinical, managerial, and policy levels (Wiig & O'Hara, 2021). The study describes another challenge is the mismatch between demand and available resources (staff shortage, limited bed availability, equipment bottlenecks), leading to difficult working conditions and compromised system functioning (Page et al., 2024). The financial burden of healthcare is escalating day by day. According to the WTW Global Medical Trends Survey 2025, costs are projected to rise by 10% annually globally, driven by increased service utilization, pharmaceutical expenses, and the adoption of high-cost medical technologies (HealthManagement.org, 2024). In the Asia-Pacific regions, costs are rising fastest, so the challenge is particularly acute due to rapid population growth and uneven public infrastructure. Over the past seven decades, healthcare systems have undergone a profound transformation in how resources are planned, allocated, and optimized. From the early adoption of operations research in clinical logistics to the integration of explainable AI in emergency response, each milestone reflects a pivotal shift in both technological capability and strategic thinking. These developments have not only improved efficiency and cost-effectiveness but also redefined equity, responsiveness, and resilience in healthcare delivery (Prabhune et al., 2025). The following table 1 traces the key historical and technological breakthroughs from foundational modeling techniques to modern predictive platforms, highlighting their significance, real-world impact, and contributions to the evolving landscape of healthcare resource optimization. Nowadays, patients expect excellence in care that requires a personalized approach, assurance of safety, and timely treatment. However, maintenance between high-quality standards, amid resources and cost constraints, is next to impossible. But the researcher explains that resilience in healthcare must include responsiveness to quality expectations even during crises (Wiig & O'Hara, 2021). But the tension between throughput and therapeutic approach depth is one of the most profound challenges facing modern health. In this landscape, AI, Machine Learning (ML), and Operations Research (OR) have emerged as powerful allies that offer data-driven solutions to optimize resource allocation, improve patient outcomes, and enhance system resilience (Ali, 2022). AI serves as the umbrella to encompass technologies that stimulate human intelligence. In the resource optimization of the healthcare sector, AI enables predictive modelling, real-time decision support, and automation of administrative tasks. For instance, AI algorithms can forecast patient admissions, supply chain disruption, and ICU beds occupancy. These insights empower the administration to proactively manage the inventory, staffing, and scheduling to minimize waste and maximize readiness (Santamato et al., 2024). ML is a subset of AI that focuses on algorithm that memorizes patterns from data without any explicit programming. It exhibits a remarkable success in forecasting patient flow, optimizing triage protocols, and identifying high-risk patients. Logistic regression and random forests are the supervised learning techniques commonly used to estimate complications or the likelihood of readmissions. Meanwhile, clustering is an unsupervised technique that assists in segmenting the population for tailored intervention. Deep learning has seen significant advances in imaging and natural language processing, further enhancing the ability to extract actionable insights from electronic health records (EHRs), clinical notes, and radiology scans (Vajjhala & Eappen, 2025). Whereas OR brings mathematical rigor in decision making, linear programming, queuing models, and simulations are instrumental in designing an efficient health care system such as OS can determine the optimal ambulances needed in a region, the best layout for emergency departments, or the most effective scheduling of surgical procedures. When integrated with AI and ML, OR models become dynamic, adapting to real-time data and evolving constraints. Together, they enabled agile, evidence-based resource management across diverse healthcare settings (Santamato et al., 2024).

Table 1. Comprehensive Milestones in Healthcare Resource Optimization (1952-2025)

Years	Milestone	Details	Significance	Example	Innovation	Reference
1952	OR enter health care	Norman Bailey applies quelling theory to outpatient scheduling	Introduce mathematical modeling for resource planning.	UK clinics reduced waiting hours & US optimized hospital facility layout	Pioneered structured decision-making in clinical logistics	(Kaplan et al., 2021)
1970	Emergence of health economics	Cost-effectiveness and utility-based frameworks formalized	Enabled relation allocation of scarce resources	WHO's Moscow seminar & Feldstein's nursing economics	Focus shifted from volume-based to value-based planning	(Organization, 2018)
1984	DRG system for Medicare	Fixed rate reimbursement linked to diagnosis	Incentivized hospitals to optimize care delivery	US hospitals reduced inpatient days, and DRG was adopted globally	Embedded optimization into financial structure	(Services, 2023)
1990	Lean & six sigma in health care	DMAIC methodology applied to reduce waste and improve workflow	Empowered frontline staff to drive efficiency	Virginia Mason cut ER wait times by 50%	Bridged industrial engineering with clinical care	(Pentecost et al., 2010)
2005	WHO Health Systems Performance Framework	Linked governance, financing, and service delivery to outcomes	Encouraged structured resource management globally	Rwanda improved maternal health via targeted allocation	Promoted equity and responsiveness as metrics	(Organization, 2018)
2010	HER	Digital	Facilitated	Kaiser	Created the	(Kelley,

	adoption accelerates	records enabled real-time data access and analytics	predictive planning and interoperability	Permanente optimized scheduling and reduced duplication	data backbone for AI and ML integration	2016)
2015	AI & ML in clinical operations	Predictive models forecast demand, optimize staffing, and manage inventory	Shifted resource management from reactive to proactive	Mount Sinai predicted ICU demands, NHS piloted ML for bed allocation	Enabled dynamic, adaptive resource orchestration	(Thomas, 2019)
2020	COVID-19 pandemic response	AI dashboards OR models deployed for ICU beds, PPE, and ventilators	Validated real-time, scalable optimization under crisis	Italy triaged ICU admissions, Pakistan used AI for ventilator tracking	Catalyzed global investment in health tech resilience	(Kamma, 2024)
2023	SHAP-Based AI models	Explainable AI used for transparent resource decisions	Improved trust and accountability in high-stakes environments	Santamat optimized emergency logistics using SHAP	Bridged ethics and analytics in clinical governance	(Ponce-Bobadilla et al., 2024)
2025	Integrated predictive platforms	Unified platforms combine clinical, operational, and financial data	Scalable tools for real-time orchestration across systems	Innovaccer is used in India for risk forecasting and diagnostics	Democratized access to advanced optimization	(Ebugosi & Olaboye, 2024)

2 Foundation of Healthcare Resource Optimization

Resource optimization in the healthcare sector is a cornerstone for efficient delivery of the services, specifically in the settings that continuously face constraints in funds, infrastructure, and workforce. In healthcare systems, the foundational pillars, such as resource allocation, workload balance, and scheduling, are the interdependent mechanisms that determine how effectively care is delivered across diverse settings (Pardede et al., 2019). Resource Allocation is the strategic distribution of limited assets (staff, beds, equipment) to meet the patients' demand. Scheduling is a temporal coordination of resources to ensure that timely services are delivered to the patient and minimize the waiting hours. Workload balancing is an equitable distribution of tasks among healthcare providers to prevent burnout and maintain quality (He et al., 2024). These mechanisms are directly influencing the operational metrics, such as patient wait times (an Indicator of system responsiveness), overflow rates (measure capacity breaches), utilization rates (reflect efficiency of resource use), and cost reduction (reducing unnecessary expenditures) (Wang & Demeulemeester, 2023). Historically, healthcare systems have always relied on static resources, manual planning, and intuition-based resource allocation. These methods offer simplicity, that often unable to adapt to fluctuating numbers of patients and emergencies. Such fixed nurse-to-patient ratios don't reflect real-time acuity levels and lead to either overutilization or underutilization. Moreover, traditional overflow management is reactive by adding beds or staff temporarily without any predictive forecast can exacerbate cost and compromise the quality of care as well (Morsi et al., 2024). Whereas the modern systems increasingly adopt AI-driven platforms, ML models, and simulation-based planning, these tools integrate real-time data to forecast demand, optimize staff schedules, and balance workloads dynamically. The PRAYON platform automates the WHO's WISN methodology, calculating ideal staffing levels based on task complexity and time requirements (Prabhune et al., 2025). AI tools can predict emergencies and preemptively adjust resource allocation and reduce waiting times and overflow rates (Soman et al., 2025). Mixed integer linear programming (MILP) models have been used to optimize staff-patient assignments while minimizing operational costs and overtime (Yinusa & Faezipour, 2023). These approaches not only improve efficiency but also increase staff satisfaction, financial stability, and patient outcomes. They are explained in detail in the following Table 2.

3 AI-Powered Hospital Bed Occupancy Forecasting

Seasonal surges in patient volume, such as influenza outbreaks, Dengue, COVID-19 waves, or any other epidemiological events, caused immense pressure on hospital resources. Predictive modeling powered by AI and ML has emerged as a transformative tool to anticipate bed demand, reduce overflow, and improve patient flow (Sarode et al., 2024). AI-based forecasting models leverage historical admission data, syndrome surveillance, and real-time patient flow metrics to estimate future bed occupancy. Techniques such as Support Vector Regression (SVR), Long Short-Term Memory (LSTM) & Bi-directional LSTM, Bayesian networks, decision trees, and deep learning ensembles have been used for resource optimization in the healthcare sector. SVR and K-means clustering have been used to forecast the weekly demand of patients for beds with high accuracy (MAPE between 0.49-4.10percent). At Geisinger Medical Center, ML-based forecasting reduced variability in bed demand and enables smooth transferring from the emergency department to post-anesthesia care units (Tello et al., 2022). LSTM & Bi-directional LSTM models trained on hourly bed-level data have shown superior performance in predicting ward-level occupancy. Real-time dashboards integrating predictive outputs to helped administrators reduce patient wait times by up to 30% during peak flu seasons (Seo et al., 2024). Bayesian networks, decision trees, and deep learning ensembles have been applied to model surge scenarios, seasonal trends, and variables like length of stay (LOS). A heart ward case study in Iran showed that predictive modeling prompted an increase in bed capacity planning from 45 to 137 beds by 2026, improving patient satisfaction and reducing overflow incidents (Mahmoudian et al., 2023). Modern forecasting systems ingest data from Electronic Health Records (EHRs), Admission Discharge Transfer feeds, and Public health surveillance systems, environmental, and mobility data. These inputs are processed using ML pipelines that continuously update predictions. Cloud-based platforms allow scalability and integration with the hospital command center for real-time decision support. Despite all of these promising outcomes, several challenges persist explained in the following Table 2.

4 Surgical Scheduling Optimization

Efficient surgical scheduling is critical for maximizing operating room throughput, improving patient outcomes, and minimizing delays. ORs generating 40% of hospital revenues, optimizing their use is necessary in both clinical and economic imperatives (Rottmann et al., 2025). In surgical scheduling, major disruptors are no-shows of patients and delays between operations. Predictive model is trying to anticipate these events by using historical data, behavioral patterns, and patient demographics. Logistic regression, random forest, and gradient boosted trees are commonly used to predict patients' no-show probabilities, accompanied by features such as appointment history, weather, socioeconomic indicators, and lead time. Systematic reviews of no-show prediction models highlight logistic regression as the most used technique, although ensemble methods are gaining traction for their higher accuracy (Carreras-García et al., 2020). Surgery duration prediction models used non-linear regression and quintile regression forests, have demonstrated high accuracy (MAE-14.9 minutes) in estimating procedure times. The causal inference technique assists in identifying which variables (patient comorbidities, surgeon experience) are influential in delaying targeting interventions. In Israel, a public hospital applied ML models to 23,000 surgery records, achieving duration prediction and identifying causal features that influence delays (Babayoff et al., 2022). Case individual scheduling models incorporate the patient-specific data to determine optimal room assignment and improve cost efficiency up to 35% as compared to the traditional scheduling method. A large university hospital in Germany used case-individual optimization to reduce scheduling costs by 35%, with 23% of attributes improved by room assignment and sequencing (Rottmann et al., 2025). Optimized scheduling has demonstrated measurable benefits across multiple domains explained in detail in the Table 2.

5 Predictive Staffing Models

Worldwide healthcare sectors are facing mounting pressure to align fluctuating patient demands with staffing levels. Predictive staffing models empowered by ML and stochastic optimization provide a data-driven solution to forecast balanced workloads, improve operational efficiency nurse and physician needs (Kabir et al., 2021). Traditional staffing relies on static ratios and historical averages, which fail to capture dynamic shifts. To control this issue, predictive models utilize the contrast of time series analysis of admission, regression models, and machine learning classifiers. Time series analysis is used for admission and discharge or transfer data, a regression model incorporates seasonality, disease prevalence, and demographics, whereas ML classifiers trained on EHRs, public health records, and census data (Ingole et al., 2025). For instance, a study using the turkey health survey applied seven ML models, including logistic regression, random forest, and XGBoost achieved the highest predictive accuracy, with recall scores of 0.90 (Orhan & Kurutkan, 2025). Once demand is forecasted, the next step is the allocation of resources, with the help of optimization algorithms to allocate staff efficiently. The key approaches include stochastic optimization, integer programming, and reinforcement learning. Stochastic optimization accounts for uncertainty in patient arrivals and acuity, generating robust staffing plans under variable conditions (Pranata & Yudhantara, 2023). Integer programming assigns shifts to minimize overtime and ensure coverage across departments, whereas reinforcement learning learns optimal staffing policies over time by stimulating outcomes and adjusting based on feedback. These techniques allow for dynamic shift scheduling, equitable workload distribution, and real-time adjustments based on incoming patient data (Marzan Kabir et al., 2021). Several healthcare systems have reported significant improvements after implementing predictive staffing models described in detail in the following Table 2.

6 Technology-Driven Resource Management in Healthcare

The convergence of the Internet of Things (IoT), cloud and fog computing and advanced AI techniques has revolutionized the healthcare resource management sector. These technologies assist in real-time monitoring, predictive analytics, and dynamic allocation of resources across emergency and routine care settings (Sitaraman, 2025). Healthcare IoT systems generate vast amounts of real-time data from wearable devices, sensors, and smart infrastructure. Managing this data efficiently requires a layered computing architecture of Cloud Computing, Fog Computing, and Edge Computing (Krishnamoorthy et al., 2023). Cloud computing provides scalable storage and centralized analytics, with the drawback of latency in critical time scenarios (Gupta et al., 2022). Fog computing bridges the gap between cloud and edge devices by processing data closer to the source, reducing latency and bandwidth usage (Qiu et al., 2021). Edge computing performs computations directly on the devices, enabling ultra-low latency response (Sodhro et al., 2019). The study proposed that fog-based architecture for the Internet of Health Things, highlighting its potential for real-time decision making in emergency care (Quy et al., 2022). Similarly, a workload-aware fog computing framework demonstrated a 45% reduction in delay and a 25% decrease in bandwidth consumption using ECG sensor data (Khan et al., 2022). Simulation tools and optimization models are a significant component for testing resource allocation strategies under varied scenarios, are Discrete Event Simulation (DES) and Agent-Based Modeling (ABM), iFOGSim and CloudSim, and Optimization Algorithms. DES & ABM replicate the patient flow and resource interactions in emergency departments (Marsha et al., 2021). iFOGSim and CloudSim simulate fog cloud environments, evaluating performance metrics like latency, energy consumption, and throughput (Moosavi & Sanchez, 2025). Optimization algorithms utilize MILP, genetic algorithms, and swarm intelligence to allocate beds, staff, and equipment dynamically (Talaat, 2022). Technology roles in healthcare resource optimization are explained in the following Table 2.

Table 2. Comparative Framework of Data-Driven Domains and Techniques for Healthcare Resource Optimization

Dimensions	Traditional Approach	AI models	Application in Healthcare	Real-world example	References
Artificial Intelligence	Simulation of human intelligence to support decision-making and automation.	Expert Systems, Natural Language Processing (NLP), Robotics, and Computer Vision.	Predictive dashboards, virtual assistants, automate triage, and clinical decision support.	AI-Powered Chatbots for symptom checking and triage (Babylon Health)	(Mahler et al., 2021)
Machine Learning	Subsets of AI learn patterns from data to make predictions or decisions.	Supervised & Unsupervised Learning	Risk stratification, readmission on predictions, imaging analyses,	TREWS system at Johns Hopkins predicts sepsis onset using HER	(Thomas, 2019)

			workflow optimization	data	
Operations Research	Mathematical modeling and optimization for effective resource allocation and decision making.	Linear program, simulations, network optimization, queuing theory	Staff scheduling, bed scheduling, ambulance routing, and supply chain optimization	Simulation-based OR model for ICU, bed allocation during COVID-19	(Kaplan et al., 2021)
Resource Allocation	Manual planning & Fixed Ratios	ML-based dynamic allocation, GNNs for network modelling	Overflow reduction, equitable distribution	GNN-based ICU transfer optimization	(Prabhune et al., 2025; Reshma Soman et al., 2025; Yinusa & Faezipour, 2023)
Scheduling	Static rosters, expert judgment	RL-based adaptive scheduling MILP optimization	OR sequencing, staff shifts, triage prioritization	Case individual OR scheduling in Germany	(Babayoff et al., 2022; Carreras-García et al., 2020; Rottmann et al., 2025)
Workload Balancing	Uniform Task Assignment	Stochastic optimization, predictive staffing models	Overtime reduction, burnout prevention	ML-based nurse staffing in a US hospital network	(Apeh et al.; Mrketing, 2025; Orhan & Kurutkan, 2025)
Bed Occupancy Forecasting	Historical Averages	LSTM, SVR, Bi-LSTM, Bayesian networks	Surge planning, ED flow, ICU capacity	Ward-level LSTM forecasting in IRAN	(Mahmoudian et al., 2023; Seo et al., 2024; Tello et al., 2022)
Surgical Duration and No-Shows	Manual estimates, reactive overbooking	ML prediction (RF, XGBoost) causal inference	OR utilization, Cancellation reduction	ML-based duration prediction in ISRAEL	(Khan et al., 2022; Nouh et al., 2025; Quy et al., 2022)
Technology Infrastructure	Centralized systems, limited automation	IoT + Fog/Cloud + Edge + Digital	Real-time Monitoring, latency reduction	Fog-IoHT for cardiac care in Mauritania	(Khan et al., 2022; Nouh et al., 2025; Quy et al.,

		Twins			2022)
Simulation Framework	Spreadsheets Modelling, Basic DES	iFOGSim, CloudSim, ABM for emergency	Scenario testing, energy-efficient planning	ECG sensor simulation with fog computing	(Khan et al., 2022; Quy et al., 2022)
Optimization Algorithm	Heuristics manual adjustment	MILP, Genetic algorithms, RL, Swarm Intelligence	Cost savings, dynamic resource use	RL-based triage optimization in ER	(Carreras-García et al., 2020; Mohamed Nouh et al., 2025; Rottmann et al., 2025)
Performance Metrics	Periodic audits, Subjective feedback	Real-time dashboards, KPI tracking	Transparency, faster decisions	Predictive dashboards for staffing ad bed use	(Prabhune et al., 2025; Quy et al., 2022; Tello et al., 2022)

7 Equity and Spatial Optimization in Healthcare

In the healthcare sector, equitable access is the most prominent verse in public health policy, specifically in the regions marked by infrastructural disparities, socioeconomic disparities, and remote geographic locations (Braveman et al., 2018). Spatial Optimization is a process to address these inequalities by strategically placing healthcare facilities to maximize coverage, minimize travel burden, and ensure service delivery across diverse populations with the help of location allocation models that offer a data-driven framework (Leitch & Wei, 2024). Location allocation models are the mathematical frameworks that assist in determining the optimal facility placement based on population demand, service capacity, and geographic constraints. These models are used to balance efficiency and equity among the underserved population (Ford-Gilboe et al., 2018). The key approaches involved are named as the Maximal Coverage model, P-median models, Capacitated Models, and Multi-period models. The maximal coverage model is used to prioritize the placement of facilities where the largest number of people can be served within a defined travel time or distance (Pan et al., 2023). P-median models involve minimizing the average distance between demand points and facilities, often used in urban planning (Oh et al., 2023). Capacitated models incorporate the facility to capacity constraints to avoid overburdening specific centers (Lin & Xu, 2023). Multi-period models account for temporal changes in demand and service delivery, helpful in dynamic or seasonal change contexts (See et al., 2024). Recent innovations have innovated the hybrid modeling by incorporating machine learning to predict demand and GIS-based accessibility scoring to refine placement decisions, such as a researcher developed a framework by the combination of mobile phone mobility data with an optimization algorithm to improve hospital placement in Erie County, New York (Salami et al., 2023). Equity-focused spatial optimization models introduce weighting mechanisms for vulnerable populations, such as elderly individuals, low-income groups, and rural residents. These models adjust catchment areas based on mobility limitations, prioritize facility placement in healthcare deserts, and use the floating catchment area method to stimulate realistic access across patterns (Abdelkarim, 2019). In Hubei, China, the researchers applied a grid to the level 2SFCA model to evaluate multilevel healthcare access. Their findings revealed core-periphery disparities, with 15.16% of residents lacking access to both primary and general hospitals (Gu et al., 2018). Reducing healthcare delivery disparities requires a multipronged approach that integrates spatial planning with systemic reforms. Such as hyper-local planning and community co-creation, engaging local stakeholders in facility planning ensures cultural relevance and trust. It prepares a resource allocation guide by using a community health needs assessment (Sun et al., 2021). Boston Medical Center's health equity accelerator exemplifies this approach that yields a measurable reduction in racial disparities in diabetes outcomes and cesarean sections (Zhang et al., 2021). Data-driven decision making uses the leverage of SDOH (Social Determinants of Health) data to identify high-need zones and integrate real-time mobility and utilization data to refine service delivery, so the predictive analytics anticipate future demands and adjust facility networks accordingly (Salami et al., 2023; Zhang et al., 2021). Policy-guided developer participation encourages public-private partnerships to expand infrastructure in underserved areas to incentivize facility development through zoning reforms and subsidies. The study demonstrated that collaborative governance in Shenyang led to the reconfiguration of 260 community health sections with an improvement of up to 98.98% (Abdelkarim, 2019). Another is multilevel service integration that aligns primary, secondary, and tertiary care networks to reduce fragmentation and use hierarchical optimization models to ensure balanced distribution across service levels, apply "Gini" coefficients and spatial autocorrelation to monitor equity outcomes (Abdelkarim, 2019). To synthesize the diverse challenges, methodological approaches, and anticipated outcomes discussed above, a conceptual framework (Figure 1). This framework illustrates how limited resources, rising demands, and systemic constraints act as critical inputs that necessitate the application of advanced optimization tools, including operations research, AI &ML, technology platforms, and spatial optimization. By systematically linking these tools with healthcare delivery, the framework highlights the pathways through which efficiency, resilience, equity, and sustainability can be achieved. Governance, policy alignment, and stakeholder engagement are shown as overreaching and cross-cutting elements, emphasizing that successful resource optimization is not only a technical endeavor but also a socio-political process requiring collaboration and adaptive management.

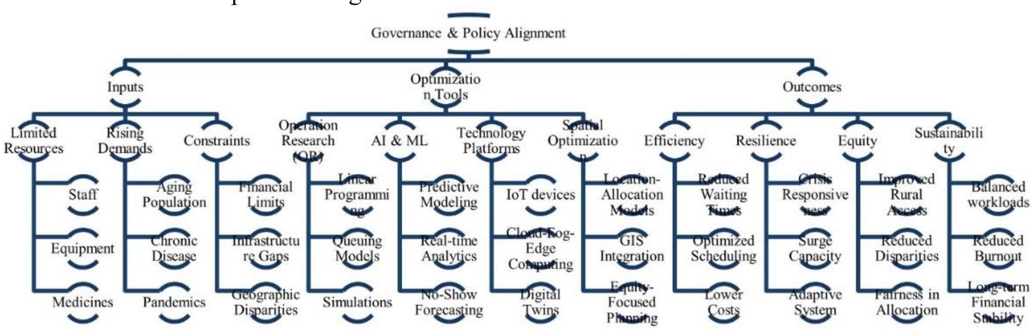

Figure 1. HealthCare Resource Optimization Framework

8 Implementation Challenges and Their Solutions

The integration of advanced analytics, AI-driven decision support, and spatial optimization into healthcare systems promises transformative improvements in access, efficiency, and equity; however, a real-world implementation is fraught with challenges ranging from fragmented data ecosystems and algorithmic bias to organizational resistance and regulatory complexity. Addressing these barriers requires a multidisciplinary strategy that blends technical innovation with stakeholders' engagement and policy alignment (Olya et al., 2022) Data integration interoperability across EHRs, insurance databases, genomic repositories, and patient-generated sources. This fragmentation impedes real-time decision-making and personalized care. But key challenges faced in this context are semantic misalignment across standards, limited cross-platform data exchange, and inadequate integration of genomic and behavioral data into clinical workflows. So the solution to these challenges is ontology-based interoperability models (enable semantic harmonization across systems), Blockchain-enabled data governance (ensure secure, decentralized access to sensitive data), and AI-supported patient-centered care frameworks (facilitate dynamic data integration for chronic disease management (Omaghomi et al., 2024). Algorithmic bias is another challenge in which AI algorithms trained on biased datasets can perpetuate disparities in diagnosis, treatment, and resource allocation. Such as an algorithm using healthcare cost as a proxy for need underrepresented black patients due to systemic access barriers (Leslie et al., 2021). The source of the bias is historical inequities embedded in training data, proxy variables that misrepresent clinical need, lack of demographic diversity in datasets. To solve these problems, we need to use fairness-aware algorithms that adjust demographic imbalance, implement bias audits during model development and deployment, promote transparency and explain ability in AI decision making (Rosemariehci, 2025b). The successful implementation of healthcare innovations hinges on human factors, specifically the ability to manage change and engage stakeholders across clinical, administrative, and community domains. Change management frameworks are used in healthcare organizations that often face resistance due to workload pressures, unclear goals, and fear of disruptions. Nearly 70% of transformation projects fail due to poor change management (Anon, 2025). Effective models in this regard are named as Lewin's Change Model (Unfreeze-Change-Refreeze), Kotter's step process (Create urgency, build coalitions, communicate vision, empower action, generate wins, consolidate gains, embed change. Engaging stakeholders such as clinicians, patients, and policymakers is vital for buy-in of sustainable strategies, including conducting a stakeholder analysis to identify influence and interest levels (Abbas, 2023). He study conducted in China emphasizes the need for interdisciplinary approaches and regulatory oversight to ensure fairness in AI-driven healthcare (Rosemariehci, 2025a). The dialed challenges and solution matrix are explained in Table 3. As healthcare systems evolve under the pressure of demographic shifts, resource constraints and technological disruption, the next frontier lies in adaptive, personalized, and real-time optimization frameworks. These innovations promise to transform static service models into dynamic, responsive ecosystems that anticipate needs, allocate resources intelligently, and deliver precision care. However, realizing this vision requires addressing persistent research gaps and fostering interdisciplinary innovations. That are in table 03.

Table 3. Emerging Models and Innovative Pathways in Healthcare Resource Optimization

Domain	Model	Objective	Innovation	Gaps	Trends	Reference
Future trends	Adaptive AI models	Real-time learning from patient feedback	High personalization and responsiveness	Interpretability and clinical integration	Explainable AI, co-designed workflow	(Rawas et al., 2024)
	Personalized resource allocation	Genomic and Behavioral data-driven planning	Precision equity	Data equity, privacy concerns	Synthetic data, transformer-based forecasting	(Mahalegi et al., 2025)
	Real-time optimization	Streaming data for dynamic decision making	Operational agility	Scalability, workflow integration	IoT-enabled triage, predictive routing	(Ali, 2022a)

9 Conclusion

Resource optimization in healthcare has evolved from static, intuition-driven planning to advanced, data-informed strategies that balance efficiency, quality, and equity. The integration of operations research, AI, and ML has transformed traditional allocation and scheduling into dynamic, predictive systems capable of responding to real-time demands. From hospital bed forecasting and surgical scheduling to predictive staffing models, optimization tools have demonstrated measurable improvements in reducing wait times, minimizing costs, enhancing patient safety, and preventing staff burnout. Likewise, technology-driven frameworks such as IoT-enabled monitoring, cloud fog edge architectures, and simulation platforms have expanded the capacity for rapid decision-making during both routine care and crisis. Equally critical is the role of spatial optimization in addressing disparities by improving access in underdeveloped and rural regions. Equity-centered approaches that integrate geographic, demographic, and social determinants ensure that optimization is not only efficient but also fair and inclusive. However, challenges remain, including fragmented data systems, algorithmic bias, organizational resistance, and regulatory complexity. Addressing these requires fairness-aware algorithms, Blockchain-enabled governance, interoperability frameworks, and structured change management strategies. Looking ahead, the convergence of predictive analytics, equitable spatial models, and collaborative governance will define the next era of healthcare resource optimization. To succeed, healthcare systems must adopt multidisciplinary strategies that combine technological innovation, policy alignment, and stakeholder engagement. Ultimately, resource optimization is not merely a technical solution but a moral and strategic imperative, one that can strengthen resilience, improve outcomes, and advance equity in healthcare worldwide.

Author Contributions

Waleed Arshad, Muneeb Arshad, Maheen Arshad, Muhammad Asjad Khan, Matiullah Khan, Fizza Shahid, Sara Aslam, and Arooba contributed to the conceptualization, literature search, review and synthesis of relevant evidence, interpretation of the literature, organization of the scientific content, and preparation of the manuscript. All authors contributed to writing—original draft and writing—review and editing. All authors read and approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

Conflict of Interest

The authors declare that they have no financial, professional, technological, commercial, institutional, or personal conflicts of interest that could have influenced the content, interpretation, or conclusions presented in this article.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data Availability

No new clinical, experimental, or patient-level datasets were generated or analysed during this study. All information discussed in the review was obtained from the published literature and publicly available sources cited in the manuscript. Additional information relating to the review may be obtained from the corresponding author upon reasonable request.

Informed Consent

Not applicable. No patients or other human participants were recruited, and no identifiable personal or clinical information was collected or analysed for this review.

Use of Generative AI

The authors declare that no generative artificial intelligence tools were used to conduct the literature review, generate the scholarly content, interpret the evidence, or formulate the conclusions presented in this article. The discussion of generative AI, artificial intelligence, and machine-learning technologies in the manuscript relates solely to their applications in healthcare resource optimization and does not constitute their use in preparing the article.

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