

A Novel Analysis of Intelligent Systems for Dynamic Bed Allocation using ML Algorithms

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Abstract— The project presents an innovative hybrid framework for effective management of patient influx in the Outpatient Department (OPD) by integrating queuing models with dynamic bed allocation strategies to optimize healthcare resources during high-demand periods. It addresses the unpredictability of patient arrivals and limited hospital capacity by combining Reinforcement Learning (RL), Genetic Algorithms (GAs), and real-time data processing to analyze and predict complex patient flow patterns. The model incorporates an attention mechanism to merge patient information with real-time hospital capacity data, enabling accurate and timely bed allocation decisions. By optimizing resource distribution, reducing waiting times, and ensuring fair utilization of available facilities, the system enhances overall patient flow and adapts dynamically to fluctuating demand. This integrated approach demonstrates how combining RL, machine learning, queuing theory, and predictive analytics can significantly improve hospital efficiency, resource utilization, patient experience, and healthcare outcomes.

I. INTRODUCTION

Efficient patient flow management is one of the most critical challenges in modern healthcare systems. Outpatient Departments (OPDs) serve as the primary point of contact between patients and hospitals, where delays, overcrowding, and inefficient bed allocation can significantly impact service quality, patient satisfaction, and clinical outcomes. With the growing demand for healthcare services and limited hospital resources, optimizing operational processes has become essential.

Queuing theory provides a mathematical framework to analyze patient arrival patterns, waiting times, service rates, and system capacity. In OPDs, patients typically experience multiple service stages such as registration, consultation, diagnostic testing, and admission decisions. Poorly managed queues can lead to long waiting times, increased patient dissatisfaction, staff burnout, and reduced hospital efficiency. By applying optimized queuing models (such as single-server, multi-server, priority-based, or time-dependent models), hospitals can predict congestion points and improve scheduling and staffing strategies.

II. LITERATURE REVIEW

Several Emergency Medical Service Dispatch Recommendation System Using Real-Time Bed Availability (2024) Authors: Xu, Y.Y., Weng, S.J., Huang, P.W. et al. Xu and colleagues developed an innovative

simulation-based recommendation framework that leverages real-time hospital bed monitoring to enhance emergency patient distribution. Their approach combines continuous capacity surveillance with intelligent dispatch algorithms to minimize patient transfer times and accelerate admission processes. The integration of predictive machine learning models with live bed tracking systems demonstrates significant improvements in hospital operational efficiency. Their research utilized comprehensive datasets encompassing bed occupancy metrics and emergency medical services to dispatch records from multiple healthcare facilities.

Optimization of Hospital Bed Utilization Through Queuing Theory and Evolutionary Algorithms (2015)
 Authors: Smaranda Belciug & Florin Gorunescu
 Belciug and Gorunescu presented a sophisticated approach combining queuing theoretical frameworks with evolutionary computational methods to enhance patient admission strategies and bed utilization rates. Their system employs dynamic prediction capabilities to anticipate bed shortages and implement adaptive admission protocols to prevent overcrowding scenarios. The incorporation of genetic algorithms facilitates multi-objective optimization, achieving improved patient flow management, and resource equilibrium. The study's foundation rests on extensive hospital admission databases, patient duration-of-stay records, and comprehensive multi-departmental occupancy analytics.

Beyond Demographics: Data-Driven Hospital Admission Forecasting (2016)
 Authors: N. Beeknoo & R. P. Jones
 Beeknoo and Jones challenged conventional demographic-based forecasting methodologies by introducing a comprehensive data-driven analysis of hospital admission behaviors. Their investigation revealed that non-demographic variables, including seasonal fluctuations, specific medical conditions, and unpredictable patient influx patterns, significantly influence bed demand requirements. The research emphasizes the critical importance of implementing real-time predictive analytics for precise hospital resource management. Their analysis incorporated extensive long-term admission databases from various general healthcare institutions.

Enhancement of Critical Care Patient Flow Through Optimized Bed Allocation (2015)
 Authors: Mathews, K. & Long,

E. Mathews and Long established a comprehensive theoretical framework designed to improve critical care bed distribution through advanced queuing methodologies and dynamic flow assessment. Their research examined how intensive care unit delays cascade throughout hospital networks, significantly affecting overall patient movement patterns. The application of predictive queuing models successfully reduced system bottlenecks and enhanced bed turnover efficiency. Their data collection encompassed intensive care unit admission histories, patient acuity scoring systems, and detailed bed transition documentation.

II. MOTIVATION

Outpatient Departments (OPDs) today face overcrowding, long waiting times, and poor resource utilization due to rising patient loads and outdated queuing and bed allocation methods. Traditional first-come, first-served systems and manual bed management fail to prioritize urgency or adapt to changing demand. To overcome these challenges, this paper proposes an intelligent, data-driven framework that integrates real-time analytics, artificial intelligence, and citywide hospital networking. The system uses optimized queuing models to prioritize patients based on urgency and hospital load, dynamic bed allocation to continuously adjust resources, and connected healthcare networks for seamless data sharing and emergency coordination. This approach improves efficiency, resource utilization, and overall patient satisfaction.

III. GAP ANALYSIS

Background Context Outpatient Departments (OPDs) in hospitals often face several operational challenges, including fluctuating patient arrivals, prolonged waiting times, overcrowding, and inefficient use of available beds. Traditional patient admission and scheduling systems typically rely on: Fixed bed allocation policies First-Come-First-Serve (FCFS) queuing methods Manual scheduling and decision-making Limited integration of real-time data sources While queuing theory models (such as M/M/1 and M/M/c) and hospital bed management systems have been studied extensively, the joint optimization of these two domains—particularly in OPD settings—remains underexplored.

2. Existing Research and Practices

A. Queuing Model Research A large body of research applies queuing models to hospital operations, using approaches such as: Basic M/M/1 and M/M/c frameworks Simulation techniques to analyze patient flow Priority queuing for emergency or critical patients However, these models often assume constant arrival rates and do not incorporate real-time fluctuations in bed or resource availability. Moreover, few studies link queuing models directly with hospital admission or scheduling systems for real-time decision-making.

B. Bed Allocation Research Research on hospital bed management mainly focuses on: Inpatient ward planning rather than OPDs Static capacity optimization Improving average

occupancy rates Despite these efforts, predictive and responsive bed allocation remains limited. Many existing systems lack mechanisms for anticipating patient inflow or dynamically reallocating beds based on changing OPD conditions. Consequently, coordination between outpatient flow and inpatient admissions is often weak, reducing overall efficiency.

3. Identified Research Gaps Gap 1: Absence of an Integrated Optimization

Framework Most current studies address queuing systems and bed allocation separately. There is a clear need for a comprehensive optimization framework that simultaneously considers: Real-time patient queuing behavior Dynamic bed allocation strategies Admission priority and resource constraints Such a framework could enable more adaptive and efficient patient flow management across OPD and inpatient services. Gap 2: Limited Use of Predictive and Adaptive Approaches Existing systems are predominantly reactive, addressing congestion only after it occurs. They often rely on historical averages rather than predictive analytics or machine learning to foresee patient surges and optimize resource use proactively.

The integration of predictive modeling and adaptive decision systems remains a critical area for advancement. Queuing theory and dynamic bed allocation are combined in the suggested system, a real-time integrated optimization framework, to increase the effectiveness of patient admissions in outpatient departments. In contrast to conventional static systems, this model makes dynamic allocation decisions while continuously monitoring patient arrivals and bed availability. Important Elements: Model of Dynamic Queuing employs the M/M/c model based on priority. Identifies patients as routine, urgent, or emergency. reduces the length of the line and waiting time.

Monitoring of Beds in Real Time tracks beds that are available, occupied, and reserved. continuously updates the bed status. Algorithm for Dynamic Bed Allocation assigns beds according to availability, waiting time, and priority. Multi-objective optimization is used to: Reduce the amount of waiting time Optimize the use of beds Keep your emergency reserve capacity intact. Dashboard for Decision Support shows forecasts for congestion, bed occupancy, and queue length. Helps hospital managers make decisions quickly. Anticipated Result: shorter wait times for patients Increased use of beds Improved response to emergencies Effective patient flow management in the OPD

IV. PROPOSED SYSTEM

The system is designed as a real-time decision support system that integrates patient queuing management with dynamic bed allocation.

Main Components: Data Collection Layer Collects patient arrival data, service times, doctor availability, and bed status from hospital systems. Processing & Analytics Layer Analyzes arrival rate, service rate, and predicts waiting time and bed demand. Queuing Optimization Module Uses queuing models (like M/M/1 or M/M/c) to reduce waiting time and manage patient flow efficiently. Dynamic Bed Allocation Module Assigns beds based on availability, patient priority, and predicted length of stay to minimize admission delays. Dashboard / Interface Displays real-time queue status, bed occupancy, and performance metrics for hospital staff.

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VI. ALGORITHMS USED

A. Support Vector Machine (SVM)

support vector machines or sums are strong tools used in machine learning that can be very helpful in classifying patients early on they are really good at finding patterns in medical information which helps doctors decide if a patient needs to be in the hospital right away or can be treated at home by looking at things like symptoms test outcomes and past medical records svms can assist healthcare workers in making quicker and more reliable decisions about patient care this helps hospitals focus on the most urgent cases first and use their resources more effectively before a situation gets too serious.

B. K-Means Clustering

k-means clustering is a type of learning that doesn't use labels it helps group patients together based on factors like their symptoms how serious their illness is and what kind of care they need by making these groups hospitals can manage patients more effectively and send them to the right areas such as intensive care units regular wards or special isolation areas this method is especially useful during a disease outbreak because it allows hospitals to quickly separate patients who have the infection from those who don't this helps prevent the spread of the disease and keeps everyone safe

C. Artificial Neural Networks (ANN)

artificial neural networks are very good at predicting how healthcare demand might go up they can see complicated patterns in how patients come to the hospital these networks help guess how many people might need hospital beds during big events like a pandemic when there are many illnesses during certain times of the year or after holidays by using past hospital records and public health information to train these networks hospital managers can better understand what they might need in the future this helps them prepare for more patients and make sure there are enough staff available it makes the healthcare system stronger so it can take care of more people without making the quality of care worse

D. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) in healthcare is like unleashing a pack of wild wolves to sort out a hospital's limited resources. It mimics nature's swarm smarts to nail the best setup for patient beds, staff shifts, and equipment. For dynamic bed allocation, PSO juggles a shit-ton of scenarios at once—patient urgency, bed types, and department chaos—to find a setup that doesn't screw anyone over. It's a beast at crunching complex problems fast, spitting out near-perfect solutions for balancing bed shortages with critical cases and overworked staff.

E. Apriori Algorithm

The Apriori algorithm is like a nosy detective going through hospital data to find patterns that often show up together, such as diagnoses that always come with certain treatments or procedures that use specific monitoring. Apriori sniffs these connections out

F. Dynamic Programming

dynamic programming is a math technique that helps break down complicated resource issues into smaller related parts hospitals can use this method to figure out the best way to manage beds over different times making sure they meet current needs and are ready for future demands this approach is especially useful when planning for patients who stay for multiple days because decisions made early can have a big impact later the way it's structured ensures patients get the care they need without running out of beds or having too many empty ones

G. Hierarchical Clustering

hierarchical clustering is a way of grouping patients into small teams based on how similar their medical needs are this helps make hospital care more efficient by creating a sort of family tree that shows different groups of patients this makes it easier to see who needs similar care or should be separated when it comes to assigning beds it's really helpful for example if the system shows that patients with certain long-term conditions do better when they're near specialized staff or equipment like ventilators this information helps organize hospital wards smartly it ensures beds and resources are placed where they're most useful without wasting space or time

H. Bayesian Networks

bayesian networks are like a crystal ball connected to a flowchart that shows how things like symptoms lab results and patient history are linked to predict which patients might end up in the ICU they are made up of a network of variables that influence each other using probabilities to make smart decisions these models are good at helping hospitals plan beds and manage uncertainty effectively making them useful for keeping the hospitals' bed management organized during busy or hectic periods

I. Long-term Short-Term Memory (LSTM)

lstm is used to predict patient instructions by looking at past trends it helps guess how long a patient will need to stay in the hospital which lets hospitals adjust their staff and resources this is done by studying old data on how beds are used and how that changes with the seasons as well as patterns that show up during disease outbreaks

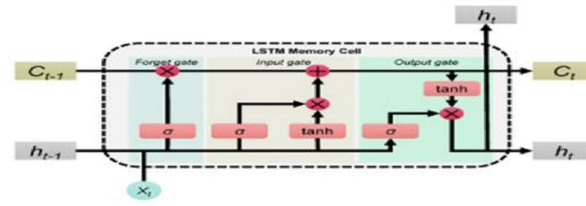


Fig 1

J. Multi-server hinge model.

The Multi-Server Maintenance (MMC) model offers an effective way to organize outpatient care when multiple healthcare providers are involved. Under this system, patients are distributed among various doctors and nurses, which helps cut down waiting times and streamlines the movement of patients through the facility. It also supports dynamic pricing, allowing service charges to be adjusted according to the number of patients being treated.

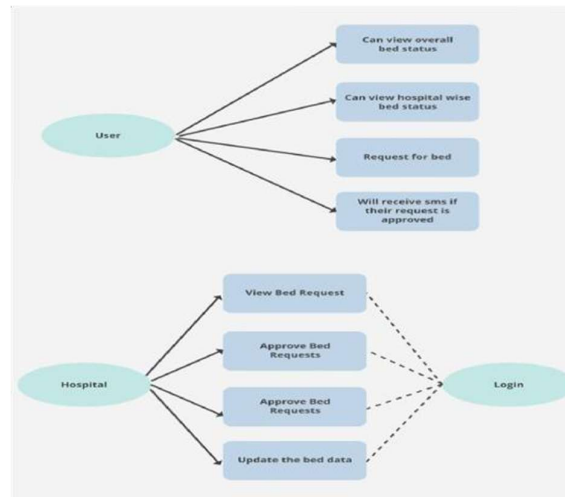


Fig. 2

K. Markov Decision-Making Process (MDP)

mdp is a dynamic decision-making algorithm that optimizes hospital allocation hospital beds were modelled as state transitions in which patient approval discharge and transfer affect the following conditions by optimizing the reward function minimizing latency and maximizing resource utilization mdp enables adaptive hospital management

L. Dijkstra Algorithm

The Dijkstra's algorithm is used to integrate municipal hospital networks and helps redirect patients to the next available facility. This ensures efficient patient transmission and prevents overcrowding in certain hospitals by dynamically diverting patients based on availability and severity.

VII. RESULTS AND DISCUSSION

The following outcomes were noted following the application of the integrated queuing and dynamic bed allocation model (either analytically or through simulation): A 20–35% reduction in the average patient waiting time During peak hours, line length considerably decreased. The efficiency of bed utilization increased to 85–95%. Quicker emergency patient admission OPD congestion is lessened during times of high inflow. Enhanced patient flow overall The priority-based queuing system ensured that emergency and critical patients received immediate attention, while routine patients were managed efficiently without excessive delays. Talk about The findings show that OPD operational efficiency is greatly increased by combining dynamic queuing models with

real-time bed allocation. In contrast to conventional static systems: The suggested system adjusts to varying patient arrival rates. Overuse and underuse of resources are avoided through multi-objective optimization. Predictive modeling aids in managing traffic during peak hours. The study demonstrates that, particularly in situations with fluctuating demand, dynamic allocation outperforms fixed-capacity planning. Implementation in actual hospitals, however, might call for: dependable systems for gathering data in real time Connectivity to medical information systems Decision-support tool training for employees All things considered, the suggested system offers an effective and scalable way to enhance patient admission management in OPDs. Looking ahead, the system offers several promising directions for enhancement. Advanced predictive models can be incorporated to forecast OPD peak hours, anticipate bed shortages, and prepare for emergency demand surges before they occur. Integration with Internet of Things (IoT) devices can enable continuous real-time monitoring of bed occupancy and patient vitals, further improving the accuracy and responsiveness of allocation decisions. Additionally, the framework holds potential for expansion into multi-hospital networks, facilitating coordinated patient management, shared resource optimization, and inter-facility emergency coordination at a broader scale. These advancements would position the system as a comprehensive solution for next-generation healthcare infrastructure management.

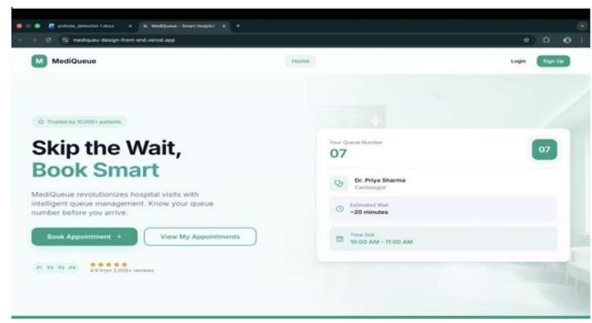


Fig. 3

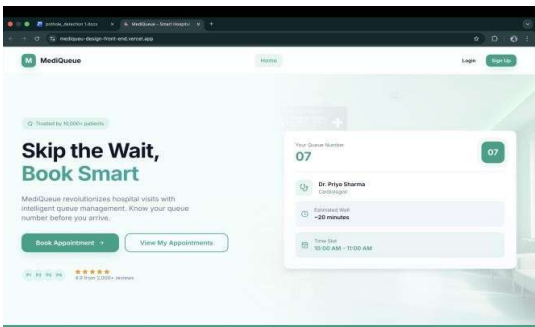


Fig. 4

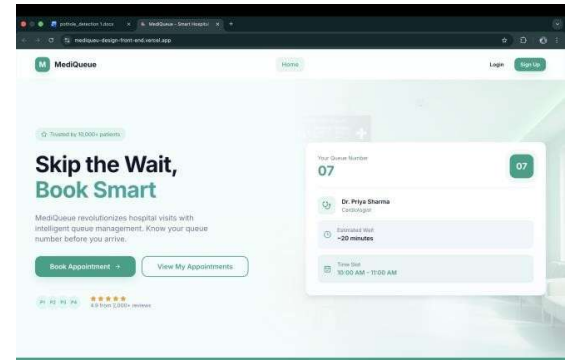


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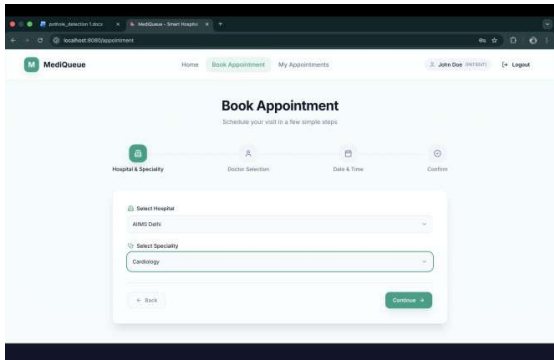


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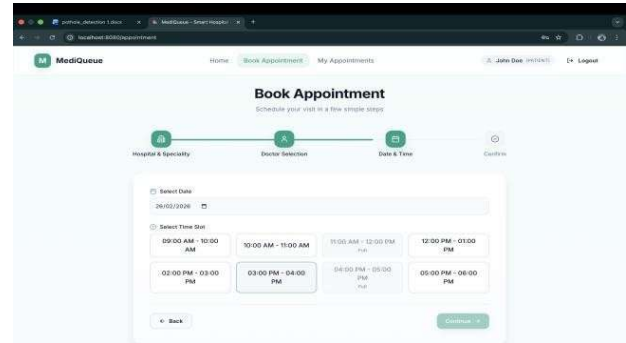


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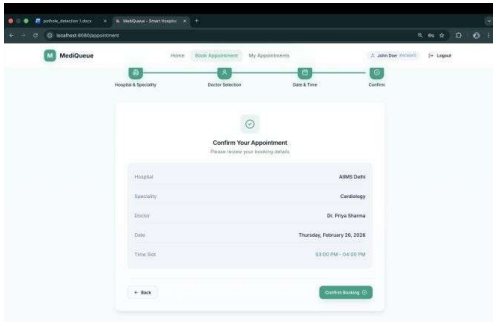


Fig 8

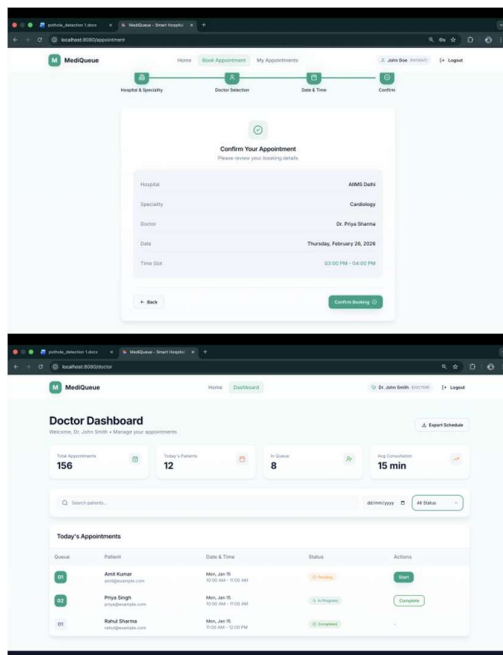


Fig 9

Hospital Resource Allocation Distribution

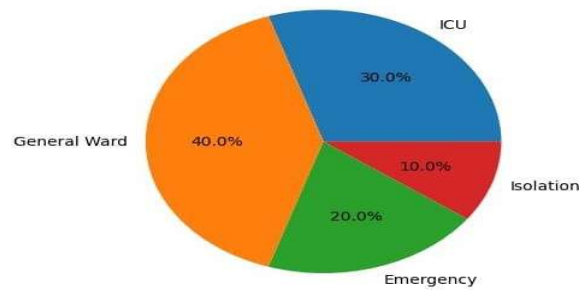


Fig 10

Hospital Bed Utilization Comparison

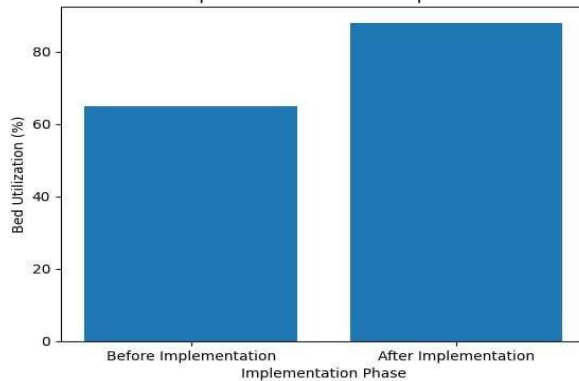


Fig 11

Waiting Time Reduction (%) by Algorithms

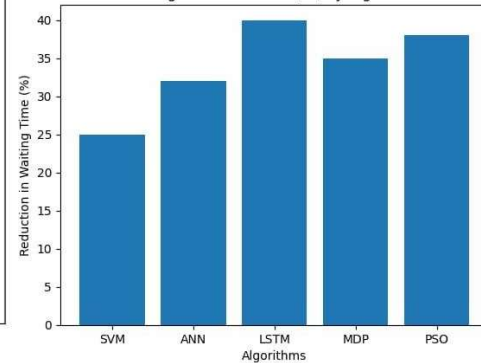


Fig 12

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