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Machine Learning in Hospital Bed Management and Patient Flow: A Comprehensive Review of Evidence Synthesis and Implementation Guidance

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ABSTRACT

Efficient hospital bed management and patient flow are fundamental to healthcare quality, operational efficiency, and cost containment. Traditional approaches such as regression modeling, simulation, and queueing theory have offered limited flexibility in addressing the dynamic and nonlinear nature of hospital operations. The rise of machine learning (ML) has transformed this landscape by enabling predictive, adaptive, and automated decision-making across multiple facets of hospital management. Recent advances demonstrate how ML supports real-time hospital intelligence through applications including demand forecasting, length-of-stay prediction, discharge readiness assessment, and dynamic bed allocation. Techniques such as random forest, XGBoost, long short-term memory, transformer models, and reinforcement learning have been successfully applied to anticipate admission surges, predict recovery trajectories, and optimize capacity distribution. These systems enhance decision support for administrators and clinicians alike, enabling faster throughput, reduced congestion, and improved coordination of resources. Emerging innovations like AI-powered hospital command centers, digital twin simulations, and federated learning frameworks are redefining operational adaptability and resilience, particularly in crisis contexts like pandemics and mass casualty events. Yet, significant translational barriers persist, including fragmented data systems, limited interoperability, and the gap between technical model design and clinical relevance. Bridging this divide requires the development of explainable, ethically governed, and clinically meaningful AI that integrates seamlessly with hospital workflows. Overall, ML is steering hospitals toward a new operational paradigm, transforming routine management into a dynamic system capable of learning and adapting in real time.

Keywords: Predictive analytics; Discharge optimization; Resource allocation; Length-of-stay modeling; Digital health transformation; Clinical decision support

INTRODUCTION

Efficient patient flow and hospital bed management determine healthcare quality, operational efficiency, and cost containment. The ability to admit, transfer, and discharge patients affects hospital capacity, clinical outcomes, and patient satisfaction. Disrupted patient flow leads to ED overcrowding, prolonged inpatient stays, and increased adverse events—challenges central to hospital operations [Tyler.S et al., 2024; Croon.P et al., 2023]. Inefficient bed allocation strains operations, limits responsiveness to demand, and compromises equitable access to care [Rengaramajunam.K et al., 2026].

Globally, hospitals face ED overcrowding, intensive care unit (ICU) bottlenecks, and delayed discharges, have been exacerbated by rising patient volumes, aging populations, and constrained healthcare resources [Rasoulian

Kasrineh.M et al., 2023; Giordano.C et al., 2021]. These pressures contribute to longer waiting times, staff burnout, and increased healthcare costs. Traditional approaches—regression-based forecasting, simulation modeling, and queueing theory—support capacity planning but rely on static assumptions and poorly capture nonlinear hospital dynamics [Bakhtiari.M et al., 2025; Samara.M.N et al., 2025]. Consequently, hospitals are transitioning from digitized systems to data-driven infrastructures enabling real-time decision support and predictive management[Koebe.P et al., 2023; Mahesh.N et al., 2024].

Advances in machine learning (ML) have introduced opportunities to predict, optimize, and automate hospital operations [Mohammad.A.A.S et al., 2025]. ML algorithms can analyze complex datasets, identify patterns, and generate accurate predictions of admission rates, length of stay, discharge readiness, and bed occupancy [Bhagat.S.V et al., 2024; Levina.A et al., 2024]. Moreover, ML-based models can continuously learn from real-time hospital data, supporting proactive decision-making and dynamic resource allocation [Li.L et al., 2022; Elhaddad.M et al., 2024]. Such capabilities position ML as a tool addressing the limitations of traditional methods and transforming hospital management into an intelligent, data-driven system [Senthil.R et al., 2024; Nasef.D et al., 2025]. This narrative review discusses current evidence on the applications of ML in hospital bed management and patient flow, highlighting predictive and optimization models, data sources, implementation frameworks, and translational challenges [Figure 1].

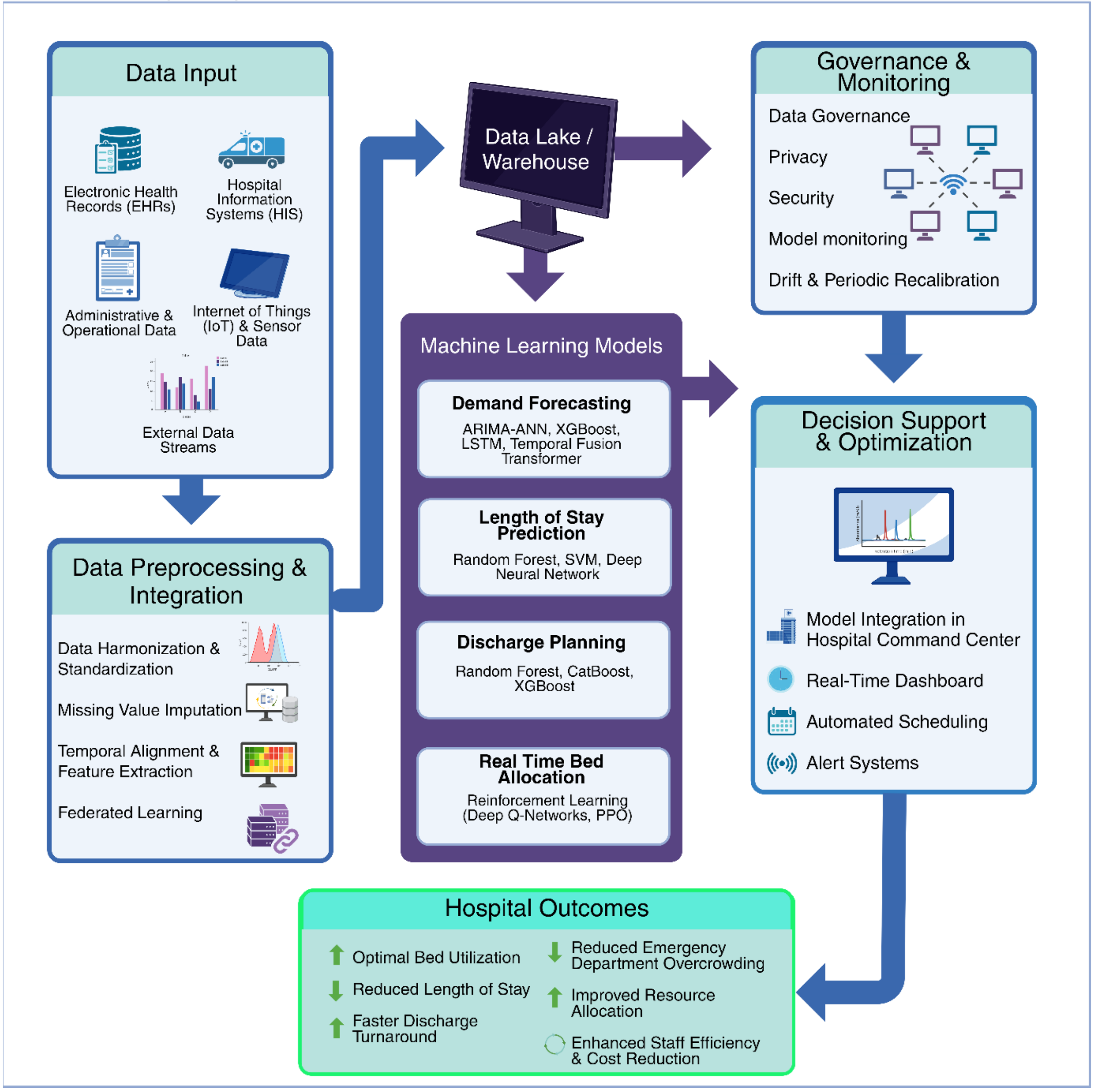

Figure 1. Conceptual Framework of Machine Learning–Driven Hospital Bed Management and Patient Flow Optimization

DIGITALIZATION TO SMART HOSPITAL

Early Digitalization

Hospital digitalization began in the 1960s–1970s, with large-scale adoption of computerized systems and connectivity emerging in the 1990s [Evans.R.S et al., 2016]. During this period, hospitals implemented electronic health records (EHRs) and hospital information systems (HIS) to replace paper-based documentation and support administrative reporting. The expansion of networked systems and internet-based data exchange aimed to improve documentation accuracy, data traceability, and regulatory compliance [Koebe.P et al., 2023, Mohammad.A.A.S et al., 2025]. International policy initiatives and digital transformation programs in Europe and East Asia further accelerated EHR adoption, increasing implementation rates by more than 40% between 2010 and 2018 [Mohammad.A.A.S et al., 2025].

Despite this growth, early digital infrastructures were not designed for analytics or operational intelligence. Reviews of European hospitals report that first-generation HIS lacked real-time data exchange and suffered from poor interoperability, even within single institutions [Klumpp et al., 2021]. Data were stored in isolated departmental systems, limiting longitudinal integration and constraining predictive or decision-support use. Similar findings indicate that data silos restricted workforce and resource management analyses, preventing reliable forecasting of staffing and bed demand [Shahzad.M.Z et al., 2023]. These limitations meant that data were largely retrospective, with most analyses restricted to descriptive statistics, simple trend summaries, and post-event audits rather than forward-looking predictions.

Hospital Information Systems

The widespread adoption of EHRs enabled the development of integrated hospital information systems (HIS). In the late 1990s and 2000s, hospitals transitioned from modular applications (e.g., radiology or billing systems) to enterprise-wide HIS supporting cross-departmental communication and shared data access [Sligo.J et al., 2017]. This integration improved continuity of care, reduced redundant data entry, and facilitated coordinated tracking of admissions, laboratory results, and discharge processes.

The evolution of HIS saw the emergence of embedded clinical decision support systems (CDSS), extended functionality beyond record management [Hak.F et al., 2022; Sutton.R.T et al., 2020]. These systems provided automated alerts, reminders, and recommendations to assist clinical and administrative decision-making. As early as the 2000s, CDSS modules were widely implemented in computerized physician order entry (CPOE) systems to prevent medication errors and improve prescribing accuracy [Sutton.R.T et al., 2020]. For example, medication-related CDSS reduced preventable adverse drug events by up to 55%, particularly through drug–drug interaction and allergy alerts [Scott.P.J et al, 2019]. Similarly, the use of CDSS integrated within EHRs decreased serious medication errors from 10.7 to 4.9 per 1,000 patient days [Kaushal.R et al., 2003]. In a meta-analysis, CDSS implementation was effective in ensuring the patients received guideline-recommended care by an estimated 5.8% improvement [Kwan.J.L et al., 2020].

HIS integration also enabled real-time monitoring of resource utilization and operational performance. Case studies in European and Asian hospitals reported reductions of 12–15% in laboratory turnaround times and improved discharge coordination following dashboard implementation [Li.L et al., 2022; Rodrigues.L et al., 2021]. The implementation of these strategies mark the shift from data documentation to data-driven management. Though during this stage, analytical capacity of HIS was rule-based, structured, and non-predictive, the framework has created technical foundation for later ML-based systems [Mahesh.N et al., 2024; Senthil.R et al., 2024].

Smart Hospitals

The transition from digitalized to intelligent hospital systems represents a key step toward smart hospital environments, where AI enables real-time decision-making and adaptive management [Levina.A., et al., 2024; Kwon.H et al., 2022]. Unlike earlier systems, smart hospitals employ AI-driven architectures that learn from clinical and operational data to optimize workflows, forecast demand, and improve resource utilization [Kwon.H et al., 2022; Elbagoury.B.M et al., 2023]. Evidence shows that AI implementation has been most effective in resource management (66.7% accuracy) and quality assurance (60.0%) [Santamoto.V et al., 2024].

Predictive analytics are used in anticipating admission surges and managing capacity fluctuations, allowing efficient allocation of staff and resources [Lazebnik.T et al., 2023; Qian.Z et al., 2021]. Machine learning models are used to predict length of stay, identify discharge-ready patients, and streamline care transitions, improving bed turnover and reducing congestion [Ahn.I et al., 2021]. Smart hospitals function as integrated ecosystems connecting Internet of Things (IoT) devices, automation systems, and AI-powered dashboards [Mohanta.B et al., 2019; Wakili.A et al., 2024]. Continuous data from sensors, monitors, and wearable devices feed into centralized platforms that generate actionable insights [Levina.A., et al., 2024; Kwon.H et al., 2022]. As connectivity deepens, cybersecurity and data protection are becoming intrinsic components of these architectures, ensuring that intelligent operations remain reliable and secure. Though it is true that published studies only focus on operational efficiency and resource allocation, with cybersecurity in healthcare has limited research development [Santamoto.V et al., 2024].

DECISION SUPPORT SYSTEMS IN SMART HOSPITAL

ML in decision support systems (DSS) has been perceived as the enablers in transforming patient flow management from reactive coordination to proactive, intelligence-driven operational control [Levina.A., et al., 2024]. By aggregating outputs from multiple predictive components, such as admission forecasting, LOS monitoring, discharge readiness, and bed occupancy prediction, the system provide a unified view of hospital capacity and throughput, allowing continuous, data-guided decision-making [Rodrigues.L et al., 2021]. Some instances include trained ML algorithms to automatically prioritize patients by clinical severity and expected resource consumption in ED settings [Chang.Y.H et al., 2022; Sung.S.F et al., 2021]. These ML models are reported enhance decision consistency during high-demand periods and align triage outcomes with downstream functions such as bed allocation, ICU referral, and discharge scheduling [Chang.Y.H et al., 2022; Sung.S.F et al., 2021]. Furthermore, integrated ML-based DSS extend to broader workflow optimization, incorporating modules for admission scheduling, dynamic bed management, LOS prediction, and early discharge alerts [King.Z et al., 2022; Sills.M.R et al., 2021]. The applications of ML-based systems and their respective functional role in hospital management are presented in **Table 1**.

Demand Forecasting

Demand forecasting enables healthcare systems to anticipate fluctuations in patient admissions and prepare resources by identifying potential surges that strain bed capacity, staffing, and supply chains [Gul.M et al., 2020]. Traditional methods such as ARIMA and exponential smoothing provide baseline temporal predictions but struggle with seasonal irregularities and sudden shocks, including epidemics and weather-related surges [Gul.M et al., 2020; Silvia.E et al., 2023]. These limitations have driven the integration of machine learning (ML) into demand forecasting to incorporate both historical and contextual information. Hybrid approaches, such as ARIMA combined with artificial neural networks (ARIMA–ANN), outperform linear regression variants (ARIMA–LR) in hospital settings [McRae.S et al., 2021; Ackermann.A.E.F et al., 2025], where it outperformed linear regression approach (ARIMA-LR) in hospital management setting [Ackerman.A.E.F et al., 2025]. Further, embedding the statistical approach with gradient boosting such as XGBoost has shown the forecasting improvement in accuracy and stability [Mitra.A et al., 2022]. Other than ARIMA, statistical decomposition model such as STL (Seasonal-Trend decomposition using Loess) can be combined with neural networks to enhance the capability in forecasting the demand of hospital bed, staff, and interventions [Li.N et al., 2022; Esghali.M et al., 2024]. The hybrid models achieved substantial error reductions and improved forecasting stability by incorporating lagged demand, census data, and external factors [Li.N et al., 2022].

Multivariate long short-term memory (LSTM) and ensemble models further improve performance in complex time-series settings. Incorporating pandemic-related variables into multivariate LSTM models reduced blood shortages by 32% and wastage by 26% [Shokouhifar.M et al., 2022]. Another study further expanded this approach through stacked ensembles combining ARIMA, ETS (Error, Trend, and Seasonality), and machine learning regressors to forecast ED attendances [Vollmer.M.A.C et al., 2021]. A study even reported the utility of automated ensemble ML platform for pediatric emergency data, where the AUCs reached >0.94 and enhancing triage-to-admission coordination [Sills.M.R et al., 2021].

ML allows the incorporation of exogenous data streams, including mobility indices, weather, holiday schedules, and local infection alerts. The research group reported low mean absolute errors, while maintaining model robustness across seasons and local events [Vollmer.M.A.C et al., 2021]. Moreover, the widely used gradient-boosted trees models (such as XGBoost and LightGBM) are often reported with SHAP-based feature importance analysis [King.Z et al., 2022; Mitra.A et al., 2022; Nevanlinna.J et al., 2025]. Attention-based architectures such as the Temporal Fusion Transformer and Informer have been proposed for hospital forecasting, offering scalability to multi-hospital datasets and interpretable temporal attention for identifying high-impact drivers of demand [Khoury.A et al., 2023; Ding.X et al., 2023].

Length of Stay Prediction

Predicting the duration of hospital stays has become a dominant component of operational planning and resource optimization [Guo.Y et al., 2020]. Accurate estimates of length of stay (LOS) allow hospitals to manage bed turnover, schedule elective procedures efficiently, and anticipate downstream service needs. Unlike demand forecasting, which focuses on aggregate admission volumes, development of LOS prediction models targets individual patient trajectories [Chang.Y.H et al., 2022, Jaotombo.F et al., 2023, Lin.W.C et al., 2022]. In this light, various predictors has been employed to enhance LOS estimation accuracy, encompassing demographic factors, comorbidities, clinical severity indices, laboratory results, and procedure codes extracted from electronic health records (EHRs) [Jaotombo.F et al., 2023]. These variables collectively capture patient complexity and disease progression, enabling data-driven assessment of hospital resource utilization.

The relationship between the aforementioned predictors and length of stay is often nonlinear. To address this, ML models are increasingly used for LOS prediction. Random forest, support vector machine (SVM), and XGBoost algorithms are frequently applied to structured clinical datasets [Jain.R et al., 2024; Kurtz.P et al., 2022]. Meanwhile, deep learning architectures, including feedforward neural networks, autoencoders, and attention-based models, are used to handle high-dimensional and heterogeneous data [Lequertier.V et al., 2021]. Deep models can integrate sequential EHR inputs, allowing dynamic updates of LOS predictions as new clinical information becomes available [Abdel-Jaber.H et al., 2022]. LOS predictors vary by care setting: physiological and organ-support trends in ICUs, surgical and anesthesia factors in perioperative care, and comorbidities and laboratory profiles in medical wards, supporting setting-specific bed management objectives [Tello.M et al., 2022], estimating recovery trajectories in surgical units [Mahmoudian.Y et al., 2023], and coordinating discharge in chronic or rehabilitative care [Soltani.M et al., 2022]. A summary of the employed ML-based predictive frameworks, primary input variables, and associated functional roles is presented in **Table 1**.

Discharge Planning

Effective discharge planning identifies clinically ready patients while minimizing premature discharge and readmissions, focusing on readiness and post-discharge needs rather than hospitalization duration, integrating medical, social, and continuity of cara factors [Levin.S et al., 2021; Wei.J et al.,2024]. In modern healthcare systems, this process has become increasingly data-driven, where the evaluation also includes forecasting post-discharge risks in real time [Cui.Y et al., 2024].

Utilizing ML allows the continuous analysis on complex, longitudinal HER data, where logistic regression with regularization, random forest, and gradient-boosting algorithms are the most common [Levin.S et al., 2021; Wei.J et al.,2024; Jiang.T et al.,2021]. The models are reported to offer interpretability, high accuracy, and adaptability to mixed data types. A study demonstrated an accurate model of real-time random forest classifiers which was integrated into hospital EHRs [Levin.S et al., 2021]. The model reduced inpatient LOS by over 12 hours through timely discharge alerts [Levin.S et al., 2021]. Similarly, other studies reported that the performance of CatBoost and XGBoost models for early identification of discharge-ready patients outperformed traditional indices such as LACE and HOSPITAL scores [Ahn.I et al., 2021, Lo.Y-T et al., 2021].

Advanced models use deep and ensemble learning to integrate multimodal clinical data and capture nonlinear patterns underlying discharge readiness [Huang.Y-Z et al., 2024; Liu.L et al., 2022]. Integrating explainable algorithms into the model enables clinicians to visualize the most influential features, such as nutritional status or comorbidity burden, enhancing trust and clinical acceptance [Pham.M-K et al., 2024]. Moreover, model performance can be enhanced by accounting for population specificity, such as neonatal or geriatric groups, where influential features may include functional or cognitive indicators [Morris.R.S et al., 2022, Hu.Y et al., 2021].

Table 1. Machine learning models and their performance used in hospital management

Reference	Location	Primary inputs	Models	Functions	Performance
[Tello.M et al., 2022]	USA (Pennsylvania)	Admission trends, census data, temporal & seasonal features	K-Means + SVR	Forecasting / Planning	MAPE = 0.49–4.10%; improved 50–70% vs ARIMA
[Soltani.M et al., 2022]	Iran, Singapore	Demographics, clinical (cancer type/stage), performance scores, service logs	LSTM (indiv. & pop.-level)	Forecasting / Decision Support	Accuracy = 69.8%; F1 = 66.8%; outperform SARIMA/VAR
[Mahmoudian.Y et al., 2023]	Iran	Admission statistics, demographics, LOS metrics, temporal variables	BN, KNN, SVM, DT, LR, SARIMA, LSTM	Forecasting / Capacity Planning	SVM (LOS Acc = 71%); RMSE ≈ 8.6–9.5
[Twumasi.C et al., 2022]	Ghana	Temporal demand data, time-series trends, corrected missing values	KNN, GRNN, NNAR, MLP, ELM, LSTM	Forecasting / Backcasting	KNN MAPE = 12.6% (best); ↑ vs ARIMA ($p < 0.001$)
[Li.N et al., 2022]	Canada (Ontario)	Laboratory (hematology, chemistry), demographics, ICU status, temporal demand	Hybrid STL + XGBoost	Forecasting / Inventory Optimization	MAPE = 15.9%; cost ↓ 43%; wastage ↓ 99%
[King.Z et al., 2022]	United Kingdom (London)	Demographics, triage data, vitals, labs, ED occupancy, temporal features	XGBoost (12 TF models), RF, Lasso LR, Poisson, survival	Forecasting / Real-Time Decision Support	AUROC = 0.82–0.90; MAE = 4.0 adm./day
[Shokouhifar.M et al., 2022]	Iran (Tehran)	Donation/demand time-series, external epidemiological (COVID-19) data	MLSTM-DN/DM vs GA & fuzzy-WOA	Forecasting / Inventory Optimization under Uncertainty	R = 0.98 (donation), 0.97 (demand)
[Vollmer.M.A.C et al., 2021]	United Kingdom (London)	Temporal demand, weather, holidays, web search trends, local events	Ensemble (ARIMA, ETS, STLM, StructTS, GLMnet, RF, GBM, KNN)	Forecasting / Operational Planning	MAPE = 6.8–8.3%; Ensemble > individual models
[Alsinglawi et al., 2022]	USA (Massachusetts)	Demographics, vitals, labs, comorbidities, admission type	RF, XGB, LR + SMOTE/ADASYN; SHAP explain.	Prediction / Resource Optimization	AUC = 0.98–1.00 (SMOTE/ADASYN RF best)
[Ebinger.J et al., 2021]	USA (California)	Demographics, labs, vitals, comorbidities, treatment variables	Ensemble ML (ENET, GBT, RF, SVM, ANN, ResNet); top: ENET Blender	Forecasting / Bed Capacity Management	AUC = 0.80–0.82; F1 = 0.78; stable calibration
[Uppal.M et al., 2022]	India, Saudi Arabia	IoT environmental sensors (temperature, air quality, humidity, fire)	RF, KNN, DT, GNB	Fault Detection / Predictive Maintenance	RF Accuracy = 94.3%; F1 = 92.0%

[Levin.S et al., 2021]	USA (Maryland)	Demographics, vitals, medications/labs, functional & mobility data	RF classifier (same-/next-day discharge)	Decision Support / Discharge Optimization	Accuracy = 0.62–0.71; LOS ↓ ≈ 12 h
[Nakagami.G et al., 2022]	Japan (Tokyo)	Demographics, nursing assessments, ADL, skin, cardiac/respiratory signs	LR, RF, Lin-SVM, XGB (5-fold CV)	Prediction / Risk Stratification	AUC ≈ 0.80; best = XGBoost
[Rafi.S et al., 2022]	France (Rennes)	Audio phonetic features (frequency, amplitude, noise, jitter/shimmer)	Bin. LR, RF (500 trees), NN (3 layers)	Classification / Emergency Detection Support	AUC = 0.75 (95% CI 0.67–0.82)
[Mahajan.A et al., 2023]	USA (Pittsburgh, Pennsylvania)	Demographics, clinical codes, medications, labs, comorbidities, social factors	LightGBM + SHAP; vs NSQIP SRC	Risk Prediction / Perioperative Optimization	AUROC = 0.95 (train/test); ↑ vs NSQIP (+0.05)
[Qian.Z et al., 2021]	United Kingdom	Demographics, comorbidities, vitals, ICU/ventilation status, mobility data	AutoML (AutoPrognosis), HGPCP, ABS	Forecasting / Capacity Planning	AUC = 0.83–0.87 (ICU/mortality); MAE ↓ 3× vs baseline
[Bishara.A et al., 2021]	USA (California)	Demographics, comorbidities, cognitive & preoperative assessments	XGB, NN, Clin-guided LR, ML Hybrid, AWOL-S	Prediction / Risk Stratification	AUC = 0.85 (XGB best); > Clin-LR/AWOL-S
[Hu.X-Y et al., 2022]	China (Jiangsu Province)	Demographics, intra/postoperative parameters, comorbidities, labs	LR, RF, XGB, SVM; LASSO feat. select.	Prediction / Risk Stratification	AUC = 0.80; best calibration (Brier ↓)
[Sills M.R et al., 2021]	USA (Colorado)	Demographics, clinical severity, ED process metrics, treatment timing	AutoML (H2O): RF, ERT, GLM, GBM, XGB, DL, Stack Ens.	Prediction / Hospitalization Decision Support	AUC = 0.91–0.94; Acc = 0.85–0.89 (autoML > RF/LR)
[Sung.S-F et al., 2021]	Taiwan (Chiayi City)	Demographics, vitals, comorbidities, triage features, medical history	LR, RF, CART, C4.5, KNN, SVM + SMOTE	Decision Support / Stroke Alert Trigger	AUROC = 0.91; AUPRC = 0.79 (LR + SMOTE best)
[Ahn.I et al., 2021]	South Korea (Seoul)	Diagnoses, labs, vitals, medications, imaging, procedural data	XGB (final) vs LR, SVM, RF, MLP; RFECV	Forecasting / Bed Management Optimization	AUROC = 0.86; Acc = 0.78 (XGB best)
[65]	Taiwan (Tainan City)	Demographics, comorbidities, functional & nutritional scores, labs, discharge data	LR, RF, XGB, CatBoost; SHAP, VIF<4	Prediction / Readmission Risk Stratification	AUROC = 0.99 (CatBoost); > LACE/HOSPITAL/PARR-30
[Lo.Y-T et al., 2021]	South Korea	Demographics, comorbidities, biomarkers, procedural/intervention data	DNN, GBM, GLM; vs GRACE	Prediction / Prognostic Decision Support	AUC = 0.94–0.97 (DNN best); > GRACE model

[Jiang.T et al., 2021]	Denmark	Demographics, psychiatric & medical diagnoses, prescriptions, socioeconomic data	Class. Tree, RF (1000 trees, 10-CV; gender-strat.)	Prediction / Risk Stratification for Suicide Prevention	AUC = 0.82–0.85; Spec = 96%; top 5% captured ≥ 38% cases
[Lin.W-T et al., 2022]	Taiwan	Maternal, perinatal, neonatal clinical data, interventions, outcomes	LR, MLP, SVM, KNN, REPTree, RF	Prediction / Length-of-Stay Forecasting	AUC = 0.72 (LR best); F1 ≈ 0.74
[Su.P-Y et al., 2022]	Taiwan	Demographics, comorbidities, vitals, hematologic & biochemical markers	SVM, RF, LGBM, DNN + RUS/ROS/SMOTE; SHAP	Prediction / Risk Stratification	AUC = 0.83 (discharge RF best); ↑ with RUS balancing
[Chang.Y-H et al., 2022]	Taiwan (Taichung City)	Demographics, vitals, triage variables, comorbidities, recent ED visits	CatBoost, XGB, RF, DT, LR; Gini, grid/rand opt.	Decision Support / Triage Optimization	AUC = 0.76 (XGB/AUH val.); Spec ≈ 83%; PPV ≈ 91%
[Eshghali.M et al., 2024]	Iran (Tehran)	Demographics, surgical/anesthetic details, staff, scheduling, traffic indicators	RF + GA + PSO (multi-phase sched.); EM cluster	Automation / Integrated Scheduling Optimization	RF Acc = 93.2%; OT efficiency ↑ 10.5%

(↑), improvement; (↓), reduction;. AUC, Area Under the Curve; AUROC, Area Under the Receiver Operating Characteristic; AUPRC, Area Under the Precision–Recall Curve; Acc, Accuracy; ADASYN, Adaptive Synthetic Sampling; ARIMA, Auto-Regressive Integrated Moving Average; DNN, Deep Neural Network; DT, Decision Tree; ELM, Extreme Learning Machine; GA, Genetic Algorithm; GBM, Gradient Boosting Machine; GRNN, General Regression Neural Network; HGPCP, Hierarchical Gaussian Process with Compartmental Prior; KNN, K-Nearest Neighbor; LACE, Length of stay, Acuity, Comorbidity, ED visits (readmission score); LASSO, Least Absolute Shrinkage and Selection Operator; LGBM, Light Gradient Boosting Machine; LSTM, Long Short-Term Memory; LR, Logistic Regression; MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error; MPE, Mean Percentage Error; NSQIP, National Surgical Quality Improvement Program; OT, Operating Theatre; PARR-30, Patients at Risk of Readmission within 30 days; PPV, Positive Predictive Value; RF, Random Forest; RMSE, Root Mean Square Error; R^2, Coefficient of Determination; RUS, Random Under Sampling; SARIMA, Seasonal ARIMA; SHAP, SHapley Additive exPlanations; SMOTE, Synthetic Minority Over-sampling Technique; SVM, Support Vector Machine; SVR, Support Vector Regression; TF, Temporally Framed; XGB, Extreme Gradient Boosting; XGBoost, Extreme Gradient Boosting Machine.

Real-Time Bed Allocation

Real-time bed allocation is a key element of hospital operational intelligence, requiring adaptive decisions that respond to dynamic patient arrivals, transfers, and discharges [Islam.M.N et al., 2022]. In contrast to demand forecasting, which provides anticipatory insights, real-time allocation operates on minute-to-minute data streams, while focusing on immediate actionable resource distribution [Rashid.Z et al., 2025]. To possess immediate adaptive response, the bed-allocation systems may run based on RL to operate in real time [Burhan.M et al., 2023]. This adaptive framework aims to adjust allocation policies as patient flows evolve. Through algorithms such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), RL agents learn to manage current bed use while maintaining steady patient flow over time, refining their actions through continuous feedback [Aliyu.D.A et al., 2024]. The main objective is to assign beds efficiently while maintaining equilibrium between cases, thereby minimizing waiting times, preventing ED boarding, and ensuring fair access across clinical units [Mulo.J et al., 2025].

Empirical evidence supports the operational value of these adaptive frameworks. For instance, integrated Random Forest prediction with GA and PSO optimization to dynamically schedule elective and emergency surgeries, improving operating theatre efficiency by 10.5% and ensuring timely treatment of emergency cases [Eshghali.M et al., 2024]. Similarly, agent-based simulation coupled with deep reinforcement learning was reported to achieve a 4.2% increase in treatment success and superior resilience under fluctuating demand and staffing conditions [Lazebnik.T et al., 2023]. Moreover, King and colleagues demonstrated that embedding an XGBoost-based admission forecast pipeline into real-time HL7 streams reduced elective cancellations and improved bed allocation precision [King.Z et al., 2022]. These models are especially effective in ICU and ED settings, where RL-based allocation reduces boarding time and improves coordination between triage and inpatient units [Sung.S.F et al., 2021; Sills.M.R et al., 2021].

Integration of ML-enabled demand forecasting, LOS prediction, discharge planning, and real-time bed allocation within hospital information systems enables continuous visualization of bed occupancy and supports automated capacity management. Examples of such integration include HL7 messaging streams, IoT-enabled occupancy sensors, and predictive dashboards embedded in hospital command centers [Bhati.D et al., 2023; Serwer.G.A et al., 2021]. Integrated with admission and discharge predictions, real-time bed allocation serves as the operational layer linking foresight to action, with ML-based optimization improving forecasting accuracy, allocation decisions, and preparedness [Mahmoudian.Y et al., 2023]. At the same time, the deployment of fully autonomous, RL-driven closed-loop control remains largely in simulation or pilot phases and has yet to become widespread in routine practice [Wu.H et al., 2023]. Thus, while these systems are transforming hospitals from reactive to more adaptive organizations, their full real-world evolution into self-regulating networks awaits further translational work on data integration, governance, and safety.

Translational Barriers

The foremost translational barrier lies within the data ecosystem. Hospital data are typically fragmented across departments and stored in heterogeneous systems. Studies across both high- and middle-income settings highlight that even high-performing models depend on extensive preprocessing pipelines and manual harmonization [King.Z et al., 2022; Lo.Y-T et al., 2021]. A more critical obstacle involves model generalizability and external validity. Many ML models are developed and validated using data from a single institution, producing algorithms finely tuned to local patient populations, resource configurations, or data capture patterns [Sills.M.R et al., 2021; Vollmer.M.A.C et al., 2021]. When transferred to other hospitals, these models frequently underperform due to dataset shift, differences in population demographics, clinical practices, and data infrastructure [Qian.Z et al., 2021; Ahn.I et al., 2021; Jiang.T et al., 2021]. The predominance of 'black-box' architectures such as deep neural networks also exacerbates this issue by producing accurate but non-transparent predictions [Sahin.E et al., 2025].

Implementing ML systems is further constrained by technical and workflow integration challenges, as legacy HIS architectures often lack compatible schemas, real-time data exchange, and robust handling of latency, missing data, and unstructured inputs [Ahmadi.A et al., 2024]. Furthermore, ethical, regulatory, and human factors remain underdeveloped in most ML deployments [Elhaddad.M et al., 2024; Evans.R.S et al., 2016; Morley.J et al., 2022]. Algorithmic bias, arising from unbalanced training data, can perpetuate inequities in triage or resource allocation, particularly in emergency or critical care contexts [Elhaddad.M et al., 2024; Abramoff.M.D et al., 2023]. Privacy and data governance frameworks often lag behind model development, leaving unclear lines of accountability when predictive decisions affect patient care [Morley.J et al., 2022; Fleisher.L.A et al., 2024, Zhang.J et al., 2023]. Additionally, limited clinician involvement in model design and insufficient training on AI interpretability reduce user confidence and hinder sustainable adoption [Garvey.K.V et al., 2022].

Resource disparities further continue to shape the global unevenness of ML integration. High cost of implementation, shortage of skilled, and infrastructural limitations, especially in low- and middle-income hospitals, restrict the diffusion of ML benefits to technologically advanced systems [Mollura.D.J et al., 2020; Nkenguye.W et al., 2025]. Studies from Iran, Ghana, and Taiwan highlight that while algorithmic innovations are increasingly feasible, deployment remains constrained by computing capacity, maintenance costs, and regulatory uncertainty [Esghali.M et al., 2024; Shokouhifar.M et al., 2022; Mahmoudian.Y et al., 2023; Soltani.M et al., 2022; Twumasi.C et al., 2022, Uppal.M et al., 2022].

Building Resilient Hospital Systems with Artificial Intellegence

Recent AI-driven forecasting models enable hospitals to adapt to sudden volume shifts by integrating real-time admissions, laboratory, mobility, and epidemiological data [89, 99, 100]. This adaptive forecasting framework was reported to yield high predictive accuracy for ICU admissions and mortality [31]. The system allows administrators to receive early warning signals that enable timely reallocation of resources, activation of contingency protocols, and proactive expansion of critical care capacity [31]. Further, RL-based adaptive system can dynamically redistribute patient loads across wards or facilities within minutes, maintaining equilibrium between emergency and elective care. For example, a study integrated RF prediction with genetic algorithms and particle swarm optimization to achieve a 10.5% improvement in operating theatre efficiency [Esghali.M et al., 2024]. Another study suggested agent-based simulation and deep RL that treatment success could increase by over 4% under fluctuating patient and staffing conditions [Lazebnik.T et all., 2023].

The role of ML-based systems was most visible during the COVID-19 pandemic, when AI models were deployed globally to predict ICU occupancy, ventilator demand, and staff shortages [Chandra.M et al., 2022;

Siriwardhana.Y et al., 2021]. At Cedars-Sinai Medical Center, ensemble ML models was utilized to forecast prolonged hospitalizations with AUCs above 0.80, informing resource prioritization and elective procedure planning [Ebinger.J et al., 2021]. Similarly, a research group integrated ensemble time-series models with public data (weather, mobility, flu trends) to forecast ED attendance and mitigate overcrowding during peak demand [Vollmer.M.A.C et al., 2021]. These deployments show that AI enhances hospital resilience, requiring adaptive integration across forecasting, optimization, and decision support to create self-adjusting systems that sustain care continuity under uncertainty.

FUTURE DIRECTIONS

The next phase of ML integration in hospital management will emphasize systems that are transparent, adaptive, and ethically governed. Interdisciplinary collaboration should be enhanced, particularly covering validation and implementation phases [Salhout.S.M et al., 2023]. In this light, the advancement of explainable AI (XAI) has become indispensable. Techniques such as feature attribution (such as SHAP and LIME), attention visualization, and counterfactual reasoning allow end-users to understand the rationale behind predictions [Amjad.H et al., 2023; Vimbi.V et al., 2024]. Empirical studies illustrate that embedding SHAP-based interpretability enhances clinical acceptance by revealing which features (e.g., comorbidities, lab results) drive predictions of surgical risk or discharge readiness [Mahajan.A et al., 2023]. Therefore, the future development of this ML-based system should combine explainability with interactive visualization interfaces, enabling clinicians to explore AI outputs in real time rather than accepting static reports.

A parallel development is the rise of real-time adaptive AI in hospital command centers, integrating live EHR, IoT, monitoring, and operational data to generate continuous recommendations [Abdulkareem.K.H et al., 2021; Ghazal.T.M et al., 2021]. Digital twin technology creates virtual, data-driven replicas of hospital systems to simulate real-time workflows, patient movement, and resource utilization [Elkefi.S et al., 2022]. These virtual environments support safe policy testing and continuous "what-if" simulations, improving hospital adaptability and emergency preparedness [Polasek.T.M et al., 2023].

Concurrently, the development of federated learning frameworks is transforming collaborative analytics across institutions [Nguyen.T.C et al., 2022; Tania.M.H et al., 2023]. By enabling decentralized model training without transferring sensitive data, federated approaches address one of the most significant barriers to AI scalability [Bashir.A.K et al., 2023]. Hospitals across regions can contribute to collective learning without violating patient confidentiality, improving model generalizability and reducing bias [Gu.X et al., 2023]. This paradigm is particularly valuable for low- and middle-income settings, where data scarcity and interoperability issues limit local model training [Tania.M.H et al., 2023]. Multi-institutional federated networks thus hold the potential to democratize AI-driven hospital management while preserving compliance with data protection regulations such as GDPR and HIPAA [Sangaraju.V.V et al., 2025].

However, the rapid expansion of AI capabilities also necessitates robust governance and ethical oversight. Regulatory standards must define principles for transparency, fairness, accountability, and data stewardship [Mourby.M et al., 2021; Garbin.C et al., 2022]. Governance frameworks should include bias auditing, model versioning, and post-deployment monitoring to ensure safety and equity. Policies must also promote inclusive innovation by supporting equitable access to AI across diverse health systems, rather than concentrating advances in high-resource settings. Pentahelix partnerships are essential for developing regulatory sandboxes [Zhang.J et al., 2023]. Such steps allow controlled experimentation and iterative improvement without compromising the systems [Mourby.M et al., 2021; Garbin.C et al., 2022].

CONCLUSION

The integration of machine learning (ML) into hospital bed management and patient flow represents a key shift from static, reactive systems to adaptive, intelligent operations. Across demand forecasting, length-of-stay prediction, discharge planning, and real-time bed allocation, ML has demonstrated consistent gains in management efficiency. However, clinical translation remains uneven due to gaps between algorithmic innovation and practical applicability. While informatics research often emphasizes predictive performance, clinical adoption requires interpretability, transparency, safety, and seamless workflow integration. Addressing this gap requires co-development frameworks in which clinicians, data scientists, and administrators jointly define objectives, evaluate outputs, and assess real-world impact. Future AI systems must therefore be explainable, context-aware, and ethically governed. These goals can be supported by adaptive command centers, digital twin simulations, and federated learning infrastructures that enable collaboration while preserving privacy. When developed with transparency and shared ownership, ML integration can strengthen the resilience of hospital management systems.

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