Artificial Intelligence in Demand and Capacity Modelling of Healthcare Systems

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***Abstract*—The increasing complexity of healthcare systems management requires the development of advanced methodologies to support efficient resource allocation, service delivery, and strategic planning. Artificial intelligence has emerged as an important tool in this domain, offering capabilities to model demand, predict capacity requirements, and inform operational decisions through data-driven insights. This article provides a comprehensive scoping review of AI-based approaches for demand and capacity modelling in healthcare systems. Specifically, it examines AI methods applied to key demand prediction tasks, including outpatient activity, emergency department attendances, hospital admissions and readmissions, and length of stay, as well as capacity planning for beds, workforce, equipment, and other critical resources. The review reports trends in AI models design, learning paradigms, performance reporting, and data usage, and highlights the relationship between demand modelling and downstream capacity predictions. In addition, the paper analyses data infrastructure requirements, commonly used datasets, and the growing role of explainable AI in supporting transparency and trust. Despite recent advances in the field, the integration of AI into healthcare systems faces significant challenges, including concerns related to privacy, ethics, data quality, interpretability, bias, scalability, policy variation, and data interoperability. Addressing these challenges is essential to develop sustainable, fair and resilient healthcare systems. Our review highlights the current state and gaps in the literature, and proposes future directions for advancing the use of AI in healthcare management systems are reviewed.**

***Index Terms*—Artificial Intelligence, Explainable AI, Machine Learning, Healthcare Management, Healthcare Demand Prediction, Healthcare Capacity Planning, Healthcare Operations Management, Medical Services.**

I. Introduction

THE management of healthcare systems is increasingly complex, driven by increasing demand, constrained resources, and the need for a high-quality and equitable care delivery. Integrating artificial intelligence (AI) tools designed to support healthcare management can improve decision making, resource allocation, and help experts accurately anticipate system needs through interpretable forecasting methods. When used correctly, AI models can uncover intricate patterns and dynamics in healthcare data while offering new avenues for proactive and efficient management.

This review contains an exploration of peer-reviewed articles reporting on the application of AI in the modelling and management of healthcare systems, focusing on the prediction of demand for services and capacity requirements. First, we explore the use of AI tools to predict patient needs, including outpatient volume, admissions, readmissions, length of stay (LoS), and demand for healthcare services outside hospitals. Then, we review studies focusing on capacity planning, addressing predictions for critical resources such as intensive care unit (ICU) beds, healthcare workforce, and medical equipment. Furthermore, this review discusses the importance of robust data infrastructures, highlighting the types of data required, relevant research datasets, and the role of explainable AI (XAI, [1]) in ensuring transparency and trust in AI tools designed for healthcare systems management. After reviewing the bibliography, including discussing the main algorithms and techniques used in different prediction problems in various contexts related to AI in healthcare management systems, the main challenges in this topic are highlighted, including model interpretability, scalability, bias and fairness [2]; concerns around privacy, ethics, and data quality [3]; interoperability across systems [4]; and effects of policy and seasonal variations [5].

Among previous reviews, Secinaro et al. [6] have conducted a large-scale bibliometric review, categorizing existing AI healthcare research into five key domains: predictive analytics, diagnostics, clinical decision-making, operations management, and patient data utilization. Most other previous literature reviews have focused on specific prediction tasks. Specifically, [7] and [8] focus on machine learning applications for hospital LoS prediction, highlighting that the performance reports of such studies should be more standardized to allow fair comparisons between approaches and avoid restrictive applications that are not generalizable for different scenarios. In [9] several statistical methods for modelling and forecasting bed capacity demand were reported. Regarding the prediction of demand for workforce capacity, the most common problem definition was to focus on supply and demand estimations, as shown in the studies selected by the literature review in [10]. Another workforce demand review, [11], focuses on nurse workforce demand prediction.

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To the best of our knowledge, there is no previous review on the use of AI tools in healthcare systems demand and capacity management. Our work provides a scoping review of the literature of AI applications for all tasks related to this area, highlighting trends and gaps in the literature as well as providing an overview of data sources and open challenges. The remainder of this article is organized as follows. Section II reviews studies on healthcare demand and capacity modelling using AI as well as a discussion about the data infrastructure characteristics and requirements. Section III provides a critical overview of open challenges for AI applications for healthcare management systems. Finally, Section IV offers conclusions.

II. Healthcare Systems Modelling With AI

Based on the World Health Organization (WHO) [12]–[14], a healthcare system can be structured into nine major areas, namely the governance and policy, health financing and payments, service delivery, health workforce, information systems, quality and safety, medical products - infrastructure - supply chain, public health and prevention, and research and innovation. The relation of demand modelling and capacity modelling with each of these areas is illustrated in Fig. 1.

A. Demand Modelling

Demand modelling in healthcare systems primarily aims to predict patient numbers, which include the number of outpatients, admissions, readmissions, length of hospital stays and services outside hospitals. Forecasting based on AI models have become essential in providing advanced accuracy and flexibility in predicting patient demand and optimizing resource allocation.

1) Emergency Department and Outpatients: Outpatient care refers to medical services in which a patient receives treatment without an overnight hospital stay. The outpatient services include consultations, diagnostic tests, minor surgeries, and follow-up appointments. The outpatient demand is significantly affected by the accessibility of primary healthcare services, ambulatory care, and number of referrals. Thus, predictions of outpatient numbers are typically based on historical data, seasonal trends, and demographic changes, and often are made daily, weekly, or monthly. Common modelling approaches include regression analysis for predicting patient inflow, time-series forecasting for capturing seasonal trends, and simulation models for evaluating the impact of healthcare policies. AI-driven approaches are applied to predict outpatient numbers, reduce waiting times and improve patient scheduling.

XGboost (XGB) regressors were used in both [15] and [16] to predict the volume of outpatient appointments, with the latter reporting 4.47% Mean Absolute Error (MAE). In [17], Random Forests (RF) and XGB classifiers were used to predict outpatients' low or high clinic wait times, reporting 85% accuracy for the RF, and 86% for XGB. In [18], the task of predicting outpatient wait times was defined as a regression problem, with the best performing XGB model achieving 5.06% MAE. In [19], a bagging classifier outperformed other algorithms on predicting missed outpatient appointments, achieving 98.5% accuracy. A bagging RF used to predict missed outpatient appointments achieved 84.8% accuracy in [20].

In [21], a Long Short-Term Memory (LSTM) neural network was employed to predict daily Emergency Department (ED) admissions, and achieved a mean error of 5.13 patients. A Convolutional Neural Network (CNN) classifier predicting ED admissions was presented in [22], achieving 86% AUC. In [23], an XGB model was used to predict ED admissions within different time intervals, with the best XGB model with AUC 84% at triage and 86% at 2 hours after ED registration. In [24], a retrospective multi-centre study across two EDs was performed, with XGB outperforming alternative methods with a MAE of 2.63–2.64 for predicting ED admissions. In [25], an ED admission prediction pipeline combining patient-level XGB admission probabilities to forecast total emergency admissions achieved MAE of 4.0. A Generative Adversarial Network (GAN) in [26] was used to predict ED admissions, achieving minimum Symmetric Mean Absolute Percentage Error (SMAPE) equal to 6.99. In [27], XGB and Deep Neural Networks classifiers both achieved 0.92 AUC. In [28], a SVR model was for ED admission predictions in medical and surgery ward in three different hospitals, with these predictions being linked to workforce demand prediction, namely optimising the shifts doctors in the ED, with the SVR model obtaining the best results overall, including 5.6% MAPE for medical demand. In [29], an AI-driven system combining 20 forecasting models for predicting admissions at a paediatric ED achieved R^2 up to 75%. A benchmark for ED prediction was proposed in [30] using MIMIC-IV-ED, establishing open-source standardised pipelines for hospitalization, critical care, and LoS prediction that enable reproducible, fair comparisons across methods.

2) Hospital and ICU Admissions: Hospital admissions and disease-specific admissions prediction approaches using machine learning have been explored.

In [31] a LSTM model was employed to predict inpatient numbers based on historical admission records. In [32], XGB was used to predict hospital admission, achieving 87.8% AUC. Unplanned hospital admissions over 12 months were predicted using Logistic Regression (LR) with forward selection in [33], achieving 69% AUC. In [34], several classifiers employed for admission prediction were compared, with the Decision Tree (DT) classifier achieving the best AUC equal to 89%. In [35] the admission prediction problem was defined as a multi-class classification to predict the ward of admission within a hospital, with seven classes, with a Deep Neural Network (DNN) model achieving up to 78% AUC. A hybrid architecture combining modified versions of CNNs and LSTM was proposed in [36] to predict the number of admissions, with minimum Mean Absolute Percentage Error (MAPE) equal to 12.96 hours in 4-week forecasts. The XGB was the best-performing classifier on admissions predictions in [37], with 80% accuracy. XGB classifier was also used in [38] to predict hospital admissions with up to 82% accuracy and to predict the admitting ward with 86% accuracy. In [39], machine learning models were used for predicting ICU admission within 24 hours and other demand tasks, with its GBT model achieving 97.7% AUC.

A stacking ensemble model in [40] forecasts cardiovascular admissions with MAPE equal to 9.679%. In [41], a random effects LR model predicting admissions after an out-of-hospital cardiac arrest achieved 77% AUC. A deep neural network based on entropy regularization in [42] focusing on admission prediction for dementia patients, achieved accuracy equal to 75.9%. In [43] a LR model with backward selection for prediction of unplanned hospital admissions of older adults achieved 72% AUC. In [44], a CNN model was used to predict both ICU admissions and cardiac arrests using multimodal data (vitals, laboratory, imaging), with LR achieving admission prediction with 89.9% AUC at the highest time resolution.

ICU admissions were predicted in [45] using Support Vector Machines (SVM), reporting 0.84 AUC. A Clinical Decision Support System based on evidential reasoning to predict the probability of ICU admissions was proposed in [46], achieving a Mean Squared Error (MSE) of 0.25. In [47] several classifiers were compared on predicting the risk of ICU admission of COVID-19 patients, with XGB achieving the best AUC equal to 98%. In [48], several classifiers for prediction of ICU admissions were compared, with XGB outperforming other models with 94.1% AUC. A statistical model to predict ICU care admission of COVID-19 patients presented in [49] achieved 75% accuracy. In [50], different tree-based classifiers predicting ICU admission of COVID-19 patients were compared, with the standard Decision Tree achieving 84.5% AUC. In [51] the XGB model outperformed other models on the prediction of ICU admissions of COVID-19 patients achieving 89.2% AUC. COVID-19 admission prediction among suspected cases in [52] achieved 96.1% accuracy using ensemble classifiers. In [53], an AutoML model that compares and selects predictors in a data-driven way achieved AUC 83.5% for ICU admission prediction. In [39], machine learning models were used for LoS prediction (short-term discharges and long-stay patients) and other demand tasks, with its Gradient Boosting Tree (GBT) model achieving 82.2% AUC.

3) Readmissions: Several hospital readmission prediction approaches have been reported in the literature, using machine learning algorithms.

In [54], different classifiers were compared for the task of predicting readmission of diabetic patients, with XGB achieving the highest accuracy equal to 65.1%. An ensemble of XGB, RF, and AdaBoost were employed in [55] for acute 30-days readmissions prediction, reporting 75.3% AUC. A CNN was used in [56] to learn feature values from time-series data, and a Multilayer Perceptron (MLP) NN model trained with this

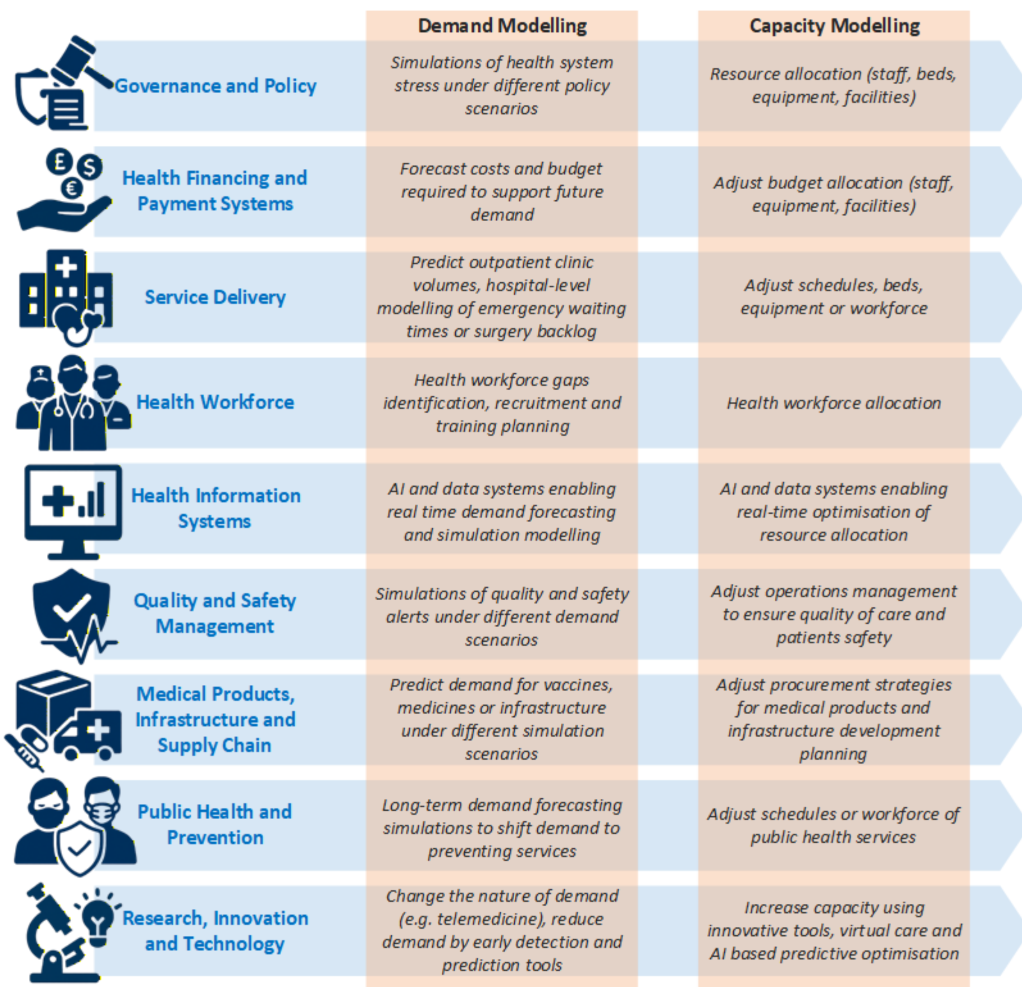

Fig. 1: Demand and capacity modelling in the structure of a healthcare management system.

data achieved 70% AUC for 30-days readmission prediction. In [57], XGB outperformed RF and LR predicting readmission within 72 hours, achieving 76% AUC. A Multimodal spatio-temporal graph neural networks (MM-STGNN) model was used in [58], achieving 79% AUC in predicting 30-day hospital readmissions. A CNN model for 30-days readmission prediction presented in [59] reported 85.8% AUC. In [60], an XGB classifier model was used to predict readmissions, achieving 84.9% AUC. In [61], a Recurrent Neural Network (RNN) model was used to capture semantic relations between medical codes for hospital readmission prediction, achieving maximum AUCs equal to 64% and 70% on the MIMIC-III [62] and the CKD [63] datasets, respectively. A different approach was proposed in [64], where the source data for predictions is plain-text discharge summaries, with a Natural Language Model used to identify key features in medical data records, and used by a LR model achieving 70% AUC for readmission prediction. In [65], gradient-boosting models incorporating wearable sensor data were applied to predict 90-day unplanned hospital readmission, achieving 83%. AUC. Transformer-based language models such as ClinicalBERT ([66]) and BioBERT ([67]) have been employed for readmission prediction from text-based discharge data in [68], reporting 73.5% AUC.

In [69], XGB achieved 58% AUC on prediction of readmission of diabetic patients, and 62% AUC on non-disease specific data. In [70], XGB achieved the best result for 30-day prediction of readmission of diabetic patients, with 66.7% AUC. A Deep Random Forests approach was used in [71] to predict readmission of diabetic patients, reporting 72.6% AUC. In [72] Genetic Algorithms combined with SVM were utilised to predict readmissions of diabetic patients, with both RF and the proposed method achieving 74% accuracy. In [73], a Gradient Boosting Machine (GBM) model was employed to predict diabetic patient readmissions, achieving 84.3% F1-score with measures in place to promote fairness across demographic groups. In [74], XGB served as a meta-learner within a stacking framework to predict emergency readmissions of heart disease patients, achieving 88% accuracy. In [75], a federated learning approach was employed to predict readmissions of diabetic patients, preserving data privacy across institutions, with an ANN model achieving 69.8% AUC, lower than centralised baselines, which is consistent with the federated privacy-accuracy trade-off. In [76], an adaptation of the temporal deep adaptation network (DAN) algorithm was applied to predict hospital readmissions of diabetic patients, achieving 85% F1-score. A semantic-based Recurrent Neural Network (RNN) framework presented in [77] reported up to 92.3% AUC on prediction of readmissions of patients with chronic kidneys diseases. In [78] XGB outperformed six other classifiers on predicting COVID-19-related readmissions, reporting 91% AUC. In [79], RF were used to predict readmission for patients with sepsis, using clinical and wearable sensor data, achieving 85% AUC. In [80] chronic obstructive pulmonary disease readmissions prediction was performed using LR with time-series data achieving 78.6% AUC.

4) Length of Stay: Estimating the LoS of patients is essential for healthcare providers and administrators, as it is highly correlated with the demand for resources. Machine learning has been applied to help predict the expected LoS of patients using data such as demographics, diagnosis, comorbidities, procedures and laboratory exam results.

LoS prediction can be considered as a classification problem, usually a binary classification of short/long stay. Among studies that model LoS prediction as a classification problem, XGB achieved the best performance among methods used in [81] (81% AUC) [82] (98% accuracy), [83] (AUC varying between 60% and 65%, with varying class thresholds). RF models had the best performance in [84] (75% accuracy), [85] (81% AUC), and [86] (76.9% accuracy). Some studies define three LoS classes instead of two (i.e., short, medium and long stay), such as in [87], which uses a generative adversarial network model that achieves a combined F1-score of 58%. In [88] an XGB achieved 89% combined F1-score, and in [89] XGB model achieved 87%, both for the 3-class prediction approach. In [90], different machine learning methods were used to predict the LoS of elective admissions, with a Bayesian Network model achieving 90% AUC.

LoS prediction can be considered also as a regression task, making a numerical prediction of the number of days (or hours) the patient is expected to stay at the hospital. Among those, tree-based regression algorithms were often employed by studies, namely decision trees in [91] (R^2 score 0.41), RF in [92] (several models created for different departments, achieving up to 61% accuracy) and [93] (R^2 score 77.8%), XGB in [94] (R^2 score 37.5%), and Boosting Gradient Forests Machines in [95] (90% accuracy). Studies that choose tree-based ML algorithms or other interpretable models, such as graph networks [96], tend to include analyses of the top predictive features in the data, which can generate important insights into the prediction problem. A regression RF model was used in [97] to predict LoS of paediatric clinic patients reporting MAE of 3.51 days.

Conversely, "black-box" algorithms were also used for LoS prediction in both regression and classification contexts, such as Linear Regressors in [98] (Root Mean Square Error, RMSE, of 8.6), Logistic Regressor in [99] (AUC 81.8% for classification), Support Vector Machine in [100] (84.5% regression accuracy). Several types of Neural Networks (NN) algorithms were also employed, such as Multilayer Back-end in [101] (78,2% regression accuracy), Feed-forward in [100] (93.7% regression accuracy), Back-propagation [102] (MAPE 14.8%). The two most common NN picks, however, are algorithms devised for time-series data, namely Convolutional Neural Networks (CNN), used in [103] (MAE 22.8%) and [104] (R^2 86.7%) and LSTM, used in [105] (RMSE 0.077) and [106] (MAE 4.19 for e-ICU dataset and 5.11 for MIMIC dataset).

5) Services outside hospitals: Demand prediction in healthcare services outside the hospital settings, e.g. home and community health services, remote patient monitoring, social care, special care, has also relied on AI-based predictions to enhance patient outcomes, increase accessibility, and optimize healthcare delivery. Remote monitoring patient systems using machine learning have been studied in [107] and [108].

Non-hospital medical services demand forecasting have been presented in [109] and [110] using machine learning methods. Demand forecasting for staff in home-care services has been proposed in [111]. In [112], RF was used to predict whether older adults in a community would require medical services. In [113], an ensemble-based method was used to predict the hours of home care services received by citizens, achieving a AUC of 71.5% with an ensemble of LR and RF models. A machine learning model (XGB-based "Friedman Score") to predict yearly primary care utilisation categories (low, high, very high use) was proposed in [114], achieving AUC of 0.81–0.89 with SHAP analysis identifying medication usage, age, and chronic disease burden as dominant predictors, as a proactive care planning tool. For long-term care planning, a model to estimate future demand and supply of healthcare services at the population level was proposed in [115], integrating demographic projections with service utilisation rates to forecast speciality-level gaps at regional health planning.

6) Current Limitations in Demand Modelling: Although the previous studies in demand modeling using AI models offer promising results, there are limitations that would affect real-life deployment.

Across outpatient prediction studies, models primarily rely on aggregated administrative data, appointment schedules, historical visit patterns, wait-time logs, and basic patient demographics, with limited use of clinical or behavioural features. While these approaches achieve substantial accuracy in forecasting demand, wait times, and no-shows, they are often constrained by static historical assumptions, leaving aspects such as real-time responsiveness, integration with scheduling systems, equity impacts, and clinician or patient-facing decision support largely unaddressed. Regarding the appropriateness of specific AI methods in demand prediction, there is no sufficient evidence of specific ML algorithms' outperformance across different tasks, as the presented methodologies are data-driven, although there are algorithms that appear as the best performing ones more frequently than others (e.g. XGB on LoS and readmission prediction).

Regarding ED demand forecasting, the majority of admission models reviewed are static classifiers applied at a single time point (e.g., triage or admission), ignoring the dynamic, longitudinal nature of clinical deterioration in hospitals. Temporal modelling approaches such as LSTM and transformer-based architectures can capture these dynamics but are underutilised comparing to standard ML algorithms. A systematic review of 31 studies on ML models predicting inpatient admissions from ED triage data (AUC 0.81–0.93) found that only 23% met criteria for rigorous methodology, with the remainder exhibiting a high risk of bias—particularly in analysis and handling of missing data [116]. This raises concerns about the reproducibility and deployment readiness of reported results. Moreover, only one reviewed study ([39]) explicitly linked hospital admission predictions to downstream capacity planning outputs (bed allocation, staffing, discharge scheduling). This represents the most critical gap from a systems perspective, i.e. predicting admission probability at the patient level does not directly translate into actionable capacity management without aggregation, uncertainty quantification, and integration with resource scheduling systems.

Critical limitations of the proposed methods for readmission prediction are also notable. In specific, the definition of readmission is inconsistent across studies, as there is no consensus on the time-window of readmission prediction (although 30-day prediction is the most common), or on whether unplanned or all-cause readmissions should be predicted, further fragmenting the literature. Moreover, few studies attempt to model the causal pathways to readmission. Most approaches treat readmission prediction as a supervised classification problem without distinguishing preventable readmissions (for which intervention is possible) from unavoidable ones (e.g., disease progression), thus limiting clinical usability. Additionally, wearable sensor data offer the potential to extend prediction beyond the hospital stay to recovery, but remain limited to small, for highly selected patient cohorts under narrow research protocols [65], [79].

Limitations and gaps can be found in the studies for LoS prediction as well. In detail, the prediction at admission versus at discharge represent fundamentally different problems. Pre-admission LoS prediction (e.g., from elective booking data) is operationally valuable for scheduling but has inherently high uncertainty, whereas post-admission prediction (using evolving clinical data) is more accurate but provides less time for capacity adjustment. Moreover, the regression formulation of LoS is under-represented compared to classification. The regression metrics reported (R^2 ranging from 0.41 to 0.778) indicate modest predictive power for the exact number of days, which may be attributed to the high variance of LoS distributions (strongly right-skewed, with rare very long stays driving most variance). Models that explicitly account for this distributional structure, such as survival analysis approaches or quantile regression, remain rare in the literature despite being methodologically appropriate. In addition, LoS prediction is rarely integrated into the downstream capacity planning pipelines. Predicted LoS values are the natural input for bed occupancy forecasts, yet only a minority of capacity modelling studies use predicted LoS as an input feature, [39]. For ICU LoS specifically, the most commonly used datasets (MIMIC-III, MIMIC-IV, eICU) are US-centric critical care registries, and models trained on these may not be transferable to ICUs of different health systems with different care protocols and case mixes.

Limitations in the proposed methods for prediction of demand in services outside hospitals can also be identified. Specifically, data fragmentation is acute in non-hospital settings. Community and home care services often rely on heterogeneous record-keeping practices, varying from paper-based care logs to proprietary social care databases that may not interoperate with EHRs or hospital systems [117], [118]. This severely limits the volume, completeness, and representativeness of data available for model training. Demand in non-hospital settings is strongly driven by social factors of health (housing, income, social isolation, caregiver availability), yet the majority of reviewed approaches rely on administrative service utilisation data without incorporating social factors. Moreover, the definition of "demand" in community settings is complex; latent demand (need for services not currently utilised due to access barriers), expressed demand (services requested), and met demand (services actually received) can diverge substantially, and none of the reviewed studies explicitly models this distinction. Furthermore, the feedback dynamics between hospital discharge and community service demand are missing from the literature. Shorter hospital LoS (driven by hospital efficiency pressures) transfers demand to community nursing, social care, and rehabilitation services, yet no study models this transfer function. This represents a critical gap for integrated care system planning.

Most demand prediction papers use proprietary institutional data, making cross-study comparisons unreliable. The MIMIC-IV-ED benchmark for admission prediction proposed in [30] represents progress, but uptake remains limited. Another limitation is that equity and fairness dimensions are largely absent from the literature on demand prediction. Most models are trained and evaluated on populations that under-represent minority demographics, and fairness metrics stratified by ethnicity, deprivation, or disability status are not reported.

B. Capacity Modelling

Capacity modelling refers to processes used to understand and plan for resources needed to meet patient demand. These include predicting the required number of beds in wards or ICUs, equipment, resources and workforce needs in a healthcare system.

1) Number of Beds: The prediction of the bed capacity required in a hospital using AI has been studied in the literature, with several statistical or machine learning based methodologies being proposed. The most common statistical modelling used to predict bed capacity requirement is the ARIMA method and its variations [119], [120]. In [121], a SARIMA model was used to predict bed capacity requirements using LoS predictions, reporting RMSE of 22.7 beds for the same-day prediction scenario. Other statistical methods used in bed capacity modelling are the Susceptible Exposed Infected Recovered (SIER) and the Discrete Event Simulation (DES) used in [122], the Poisson model in [123], the growth-rate model in [124], the survival analysis methods in [125] and the Erlang B method in [126].

Bed capacity modelling using machine learning is usually defined as a regression problem to perform numerical prediction, although it is possible to set a fulfilment threshold and make a binary prediction of whether demand for bed capacity is fulfilled, as was followed in [127]. The datasets used in number of beds prediction are usually time-series data and thus studies tend to employ algorithms that handle this type of data well such as LSTM [128], [129], Recurrent Neural Networks (RNN) [130], and Temporal Convolutional Networks (TCN) [131]. In [132], a Spatio-Temporal Neural Network model was used to forecast bed occupancy hours ahead, outperforming standard ML methods with a MAE of 30.92 beds. Other methods used to predict the required number of beds are the MLP [133] and combinations of MLP with ARIMA [134]. Standard regression algorithms have also been used for this task, such as Linear Regression in [98] and [135]. In [136] an RF model outperformed other candidates at predicting the weekly bed occupancy at a hospital, with MAPE equal to 3.57%. In [25] aggregated patient-level probabilities (including probability of admission) predicted using XGB are used to estimate bed capacity requirements.

A hybrid framework for ED bed capacity assessment was presented in [137], with an ensemble approach combining ML and statistical models yielded the most robust forecasts (MAPE 2.53% for daily bed usage). Bed capacity forecasting using ML and deep learning was benchmarked in [138] using COVID-19 hospitalization data, with a SVR model outperforming other ML algorithms with average MAPE 1.42%. For long-term care bed planning, a simulation-optimisation approach using demographic-based demand forecasting as input was proposed in [139].

2) Workforce: Predicting the required capacity in healthcare professionals has been studied in the bibliography following different approaches and problem definitions. Supply and demand analysis is a common method used for this task, often modelled as time-series data curves fitted using statistical techniques such as demand-based projection [140], [141], stock-flow modelling [142], GM(1,1) modelling [143], and inferential statistics methods [144]. An AI-driven shift optimisation linked to demand forecasting for a paediatric ED in [29], was used to optimise scheduling for doctors and increased allocation by up to 30.4% during peak hours.

Machine learning-based methods have also been used in workforce capacity prediction. Workforce prediction can be modelled as a classification task, with the class label being defined as 'fulfilled or unfulfilled', and algorithms used for this task include rule inducers in [145] and RF in [146]. Similarly, in [147], different ML classifiers were compared on predicting whether nurse staffing at a hospital was sufficient, achieving 97% AUC. Other studies define workforce modelling as a regression problem, i.e. estimating the number of professionals required, such as multi-granular stacked regression in [148] and LSTM models in [149]. In [150], TSMixer (a time-series forecasting algorithm) models trained on hourly nursing staff records were used to predict nursing capacity using real-time absence and demand data, with MAE of 1.126 nurses.

Some studies focused on prediction problems related to workforce capacity without directly predicting it. In [151], decision tree and Naïve Bayes models were used to predict the outcome of patient visits, using workforce numbers as predictive features. RF models were used in [152] to predict the specialities of physicians, and ARIMA models were used in [153] to optimise medical staff allocation based on predicted patient flow, using synthetic data. In [28] admission predictions by SVR methods were used to predict doctor capacity requirements in medical and surgery wards, leading to a reduction of 10.8% in waiting times after the doctors' shifts were optimised using the model predictions.

Regarding the speciality of workforce, reviewed studies include prediction of required capacity in medical doctors [140], [142], [143], [144], nurses [141], [143], [145], [150], healthcare providers [143], and support staff [146], [149].

3) Equipment and resources: Capacity forecasting of equipment (other than beds) and resources for healthcare systems can be linked with workforce requirements, categorised broadly as hospital needs [154], or asset consumption [155].

Different ML-based methods have been used in equipment capacity modelling. In [156], RF was used to predict to which extent the capacity of protective equipment for healthcare providers was enough in a hospital's maternity ward. In [157], a SEIR model was used to predict the daily capacity in resources related to the pandemic (ventilators, gowns and test kits). A combination of NN and ARIMA was used in [134] to predict the availability in ventilators. A Temporal Convolutional Network was used in [131] to predict the required capacity in ventilators. Other tasks include estimating the number of B-ultrasounds for prenatal patients [158] and the daily number of calls that will result in ambulance dispatches [159].

4) Current Limitations in Capacity Modelling: A number of limitations of the approaches on bed capacity prediction reported in the literature can be highlighted. In specific, hospital bed capacity is not homogeneous, as beds differ in speciality (e.g. cardiology vs general medicine), equipment level (e.g. monitored vs standard), infection control status (e.g. isolated vs bay), and staffing intensity (e.g. ICU vs step-down). None of the reviewed studies has modelled bed-type heterogeneity at a level of granularity actionable for ward managers. Moreover, the decoupling of bed prediction from demand prediction (e.g. admissions, LoS) means that many capacity models are not actually end-to-end systems, as they require separate demand inputs and do not propagate uncertainty from demand forecasts into capacity estimates. This creates a compounding uncertainty problem, as errors in admission prediction and errors in LoS prediction both affect bed occupancy, yet none of the reviewed studies has formally quantified or propagated this joint uncertainty. Except this, hospital networks regularly transfer patients between sites based on capacity, yet the approaches in the literature treat individual hospitals as isolated systems. Multi-site capacity optimisation under demand uncertainty remains an open research problem.

A critical analysis of workforce modelling reveals a number of gaps. In detail, the proposed methods have not modelled multi-grade, multi-competency workforce capacity in a granularity sufficient for roster generation. Furthermore, operational decisions (shift-level rosters) require 24–72 hour horizons with hourly granularity, tactical decisions (agency staff procurement, bank staff activation) require 1–4 week horizons, and strategic decisions (training pipeline design, workforce expansion) require 3–10 year horizons. The reviewed studies are distributed irregularly across these horizons, with the majority of them focusing on daily-to-weekly short-term predictions, with only one ([139]) addressing the long-term strategic horizon where demographic demand growth, training pipeline lags, and workforce attrition rates are most consequential. Additionally, the methods presented in the literature have not modelled the joint optimisation of workforce and patient flow. Workforce and other healthcare capacity tasks are interdependent, as understaffing causes delays that increase LoS, which in turn increases bed occupancy and creates further demand on nursing time. This feedback loop is well understood qualitatively but has not been modelled quantitatively by any reviewed study.

Regarding equipment and resource capacity prediction, the identified limitations are highlighted. To begin with, the equipment capacity literature is dominated by COVID-19 pandemic studies (ventilators, PPE, test kits), which represent an irregular and extreme operating scenario. The disconnect between pandemic-driven and routine equipment modelling represents a significant gap. In addition, the modelling of equipment as aggregate stock (e.g. ventilator capacity) ignores the spatial distribution of equipment across wards, portability constraints, maintenance schedules, and the lead times required to procure or redeploy equipment. Moreover, the interdependence between equipment and workforce is absent from reviewed models. Equipment such as MRI scanners and dialysis machines requires specific trained operators, so capacity planning for equipment without joint modelling of operator availability is incomplete. Furthermore, perishable resources such as blood products, radio-pharmaceuticals, biologics, and single-use devices have time-sensitive demand profiles. No reviewed study modelled perishable supply chain dynamics for healthcare, despite this being a source of significant waste and patient safety risk.

Across published approaches there is a lack of integration between capacity modelling and demand modeling [160]. Specifically, in demand prediction literature the capacity planning decisions such as staffing rosters, bed allocation and surge protocol activation, operate at various time horizons simultaneously (hours, days, weeks). Demand prediction models that produce single-horizon outputs without uncertainty quantification are of limited operational value. There are few studies addressing the linkage between demand and capacity modelling, using demand related information as input feature to model capacity, as tabulated in Table I, however there is still a lack for end-to-end modelling of all related demand and capacity prediction tasks, with considerations of operational challenges for implementing suggested optimisations and of error propagation across dependent tasks. Moreover, similarly to demand prediction, no specific ML algorithm can be identified as the best one for specific capacity modelling tasks, as the presented methodologies are data-driven.

TABLE I: Linkage between demand-related information and capacity modelling. Demand information (in rows) is used as input feature in capacity modeling (columns). Approaches using ML-based demand predictions as features in capacity modelling are denoted with asterisk, while the rest are using system's demand information as features.

Demand \ Capacity	Beds	Workforce	Equipment/Resources
ED and Outpatients	[25]*, [137]* [139], [127]	[28]*, [29]* [141]	[159]
Hospital/ICU Admissions	[25]*, [39]* [98], [122–141] [137]*, [138]	[141]	[131], [134] [162–164]
Hospital/ICU Readmissions			
Hospital/ICU LoS	[39]*, [121]* [139] [127–130], [131]		[131]
S. Outside Hospital		[141]	[159]

C. Data Infrastructure in Healthcare Systems

1) Data for Healthcare Systems Prediction Tasks: The available data for healthcare systems management used in the tasks described in Sections II-A and II-B can be broadly divided into those referring to individual patients and those referring to hospitals. Patients' related data, most often used in admission/readmission and LoS prediction, include each patients' demographic features (e.g. age, sex, ethnicity, and financial state [45], [33]), event records (e.g. A&E, Inpatient and Outpatient data) and information about the patients' condition(s) (e.g. ICD diagnosis codes [32], scheduled procedures [42], vital signs [34] and laboratory exam results [25]). In addition, some AI models use information about the patients' medical history, such as comorbidities and history of treatment [11], calendar dates [37], and specifics about the disease the AI model focuses on (e.g., heart failure [41]).

AI models predicting capacity of resources and workforce use data that apply to the whole hospital such as the trends of inpatients and outpatients [34], outcome probabilities [161], and the ratio of healthcare professionals to patients [55], [71]. Bed capacity prediction models often include both patient-focused and hospital-wide categories of features, and may use predictions of different models as features in capacity modelling. Moreover, a study that focused on predicting capacity for resources and workforce included predictive features related to the COVID-19 pandemic, such as social isolation indexes and vaccination rates [122], together with typical features to support decision-making for the allocation of resources during the pandemic.

2) Datasets: Tables I and II tabulate brief descriptions of publicly available datasets used in the articles cited in Sections II-A and II-B (column 'Used In'), for demand and capacity modelling, respectively. Articles in the 'Used In' column marked with an asterisk (*) provide also the source-code.

3) Recent advances in AI (XAI, LLMs, Federated Learning): As AI becomes increasingly embedded in healthcare systems management, explainability is essential to ensure transparency, trust, and safe adoption [1], [182]. In healthcare systems management, Explainable AI (XAI) plays distinct, but complementary roles. In demand prediction, XAI supports identification of clinically meaningful predictors [70], detection of data quality issues [183], and auditing of model behaviour across subgroups [109]. In capacity modelling, XAI enables justification of resource allocation decisions [137], interpretation of key demand drivers [114], and scenario analysis [147] to assess the impact of changing conditions.

XAI techniques that have been applied in healthcare studies include SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) to explain model predictions [184], [109], for models visualization [185], user-centred XAI systems [186], XAI interfaces [187], and in counterfactual explanations [188]. A case study presented in [189] has demonstrated the impact of explainability on patient outcomes, showing increased adoption of AI tools when explanations are provided. While SHAP remains the most widely used post-hoc explanation method, many studies do not explicitly frame their contributions within XAI [190]. Extensions such as WindowSHAP [191] enhance applicability on time-series models, particularly in longitudinal ICU prediction tasks.

Across the different functions of XAI in the context of healthcare systems management context, we can highlight the following:

- **Clinical Decision Support Systems (CDSS)**: XAI enhances CDSS by making AI-generated suggestions interpretable for clinicians [192]. For example, real-time risk predictions of hypoxaemia during surgery, enabling physicians to validate AI-driven alerts before taking action [193].
- **Operational Efficiency**: Hospitals leverage AI models for patient flow optimization and resource management. XAI can support bed allocation and scheduling recommendations becoming understandable and justifiable to hospital administrators [125].
- **Ethical and Legal Compliance**: XAI assists in ensuring compliance with healthcare regulations by providing justifications for automated decisions, assisting in bias identification, and improving fairness in patient treatment recommendations [194]. However, researchers studying ethics in AI have outlined ethical risks in healthcare AI, such as breaches in patient privacy, threats to autonomy, and insufficient regulations [195].

Large-Language Models (LLMs) have also been applied in healthcare data tasks. LLMs can be used for tasks including clinical text summarization, demand forecasting assistance, and interactive decision support [196]. However, their opaque reasoning, overconfident outputs, and risk of hallucinations introduce new explainability challenges [197]. Addressing these requires safeguards such as uncertainty estimation, constrained generation, and hybrid systems where LLMs support validated predictive models. LLMs have been used in approaches for LoS prediction [84] and as data enrichment tools in admission prediction applications in [66] and [68].

Except LLMs, Federated Learning (FL) is also gaining attention within healthcare research, as it enables collaborative model training across institutions without sharing sensitive data, making it particularly suitable for demand and capacity modelling under strict privacy constraints [198]–[200]. FL has been applied in readmission prediction in [75]. However, the distributed and heterogeneous nature of FL complicates explainability, requiring methods that provide both global insights and site-specific interpretations [201].

III. Open Challenges

AI applications to healthcare systems management are primarily used to support decision-making by human experts, by providing reliable, transparent and timely information [202], [203]. Based on the literature review the following open challenges requiring further research can be highlighted.

Privacy, ethics and data quality: Due to the sensitive nature of data related to healthcare, it must be ensured that datasets used to train AI models comply with privacy laws, regulations, quality and ethics guidelines of organizations such as the HIPAA (USA) and the GDPR (Europe) [3]. Regulatory

TABLE II: Publicly Available Datasets Used in Healthcare Systems Demand Prediction Modelling

Ref	Dataset Name	Location and Timespan	Records	Description	Used in (Prediction Task and Ref)
[19]	EHR from Fundación Valle del Lili Hospital, Colombia	Colombia 2019-2022	18,587 appointments	Attendance data of no-show outpatient appointments	Outpatients: [19]*
[162]	IORD - Infections in Oxfordshire Research Database	United Kingdom 25+ years	Over 1 million patients	Records patients attending main hospitals or General Practices in Oxfordshire, United Kingdom	Admission: [35]
[163]	FAFESP COVID-19 hospitalization data	Brazil 2023	3,022 records	Demographics, clinical and laboratory exams, medical information	Admission: [49]
[164]	Kaggle's Stroke Prediction Dataset	N/A	∼5,110 patient records	Patient demographics/health features for stroke risk classification	Admission: [34]
[165]	Chronic Kidney Disease Queensland Registry	Australia 2011-present	∼7,000–11,500+ participants	Chronic kidney disease patient registry across Queensland, Australia	Readmission: [69], [61]
[166]	UK Biobank	United Kingdom 2006-2010	∼502,000 participants	Biomedical, genetic, imaging, lifestyle and linked health records	Readmission: [60]
[167]	UCI ML Repository's Diabetes Dataset	USA 1999-2008	101,766 hospital patient records	Hospitalized diabetes patient features for readmission prediction.	Readmission: [54], [69], [72], [73], [75], [70], [61]
[168]	National Institutes of Health: All of Us Database	USA 2018-present	∼633,000+ participants	Longitudinal health, EHR, survey, and wearable data	Readmission: [65], [79]
[169]	MIMIC III	USA 2001-2012	58,976 ICU stays	De-identified ICU electronic health record (EHR) data: vitals, labs, medication, codes	Readmission: [69], [64], [57], [77], [61] LoS: [106]*
[170]	MIMIC IV	USA 2008-2022	546,028 hospitalizations 94,458 ICU stays	Large integrated EHR data across hospital & ICU stays	Admission: [37] Readmission: [58]*, [68] LoS: [106]*
[171]	Statewide Planning and Research Cooperative System (SPARCS)	USA 1982-present	About 20 million patient records	Patient-level inpatient, outpatient, ED, surgeries, charges	LoS: [86], [87], [91]
[172]	National Inpatient Sample Database	USA 1988-present	>7 million patient discharge records/year	All-payer hospital inpatient discharge data	LoS: [89]
[173]	The eICU Collaborative Research Database	USA 2014-2015	∼200,859 ICU stays	De-identified ICU clinical data with vitals, labs, treatments	LoS: [106]*
[62]	Kaggle's MIMIC III Aggregated Dataset	N/A	58,976 patients	Demographics, type of admission, diagnosis, procedures, transfers, events	LoS: [104]
[88]	EHR from Cangzhou Central Hospital	China 2017-2018	18,159 records	LoS, comorbidities, insurance data for ischaemic stroke patients	LoS: [88]
[99]	National Brain Center Hospital Dataset	Indonesia	∼200 records of cerebral aneurysm	LoS, demographics and comorbidity data of cerebral aneurysm patients	LoS: [99]

TABLE III: Publicly Available Datasets Used in Healthcare Systems Capacity Prediction Modelling

Ref	Dataset Name	Location and Timespan	Records	Description	Used in (Prediction Task and Ref)
[169]	MIMIC III	USA 2001-2012	58,976 ICU stays	De-identified ICU electronic health record (EHR) data: vitals, labs, medication, codes	Beds: [122]
[174]	University Hospital Ghent COVID-19 data	Belgium 2020	1114 records	Ward, admission, discharge and length of stay data	Beds: [123]
[175]	ArcGIS COVID-19 Resources	Canada 2020-2023	6,617,095 COVID-19 cases in Canada	Number of cases, rates related to COVID-19 (hospitalization, ICU occupancy, fatality, LoS)	Beds: [122], [131]
[176]	Data from University Hospital in Baltic States	Baltic States 2015-2020	2,030 records	Nurse-to-doctor ratios, number of patients, hospitalizations, births, CT and MRI scans, labour market data	Workforce: [141]
[177]	Data from the University Hospital Augsburg	Germany 2022-2023	13,069 hourly records (18 months)	Nursing staff capacity, absences, records and calendar variables	Workforce: [150]
[178]	Data from Clinical Commissioning Groups	England 2018-2019	1,618 records	ED attendance, and capacity for GPs and emergency response	Workforce: [148]*
[179]	Medicare Fee-For-Service Public Provider Enrolment Data, CMS-USA	USA 2014-2016	564,986 physicians	Prescription and procedure Medicare data	Workforce: [152]
[180]	COVID-19 hospitalizations from HealthData.gov	USA 2020-2024	81,700 daily hospitalization records	State-aggregated time-series data of COVID-19 hospitalizations in the USA	Equipment: [157]*
[181]	NHS Ambulance dispatch data	United Kingdom 2013-2019	over 2,000 days counts of emergency calls	Use of emergency health services across the United Kingdom	Equipment: [159]*

and governance considerations are essential in shaping the feasibility of AI adoption in healthcare systems operations. Compliance with data protection regulations, accountability requirements for automated decision support, and institutional risk management policies can significantly influence model design and deployment timelines.

Interpretability and transparency: AI tools for healthcare systems management should increase focus on explainability (XAI [1], discussed in Section II-C.3) to provide the end users (healthcare workers) with actionable insights, which should be easily integrated into their day-to-day operations. To increase trust to AI models and facilitate their adoption, XAI solutions must address the ethical and legal concerns of incorporating automated decision support tools into healthcare management processes.

Flexibility and scalability: Although the developed AI tools aim to integrate within existing systems (e.g., using predictive features already provided by the EHR system at the target hospital), AI tool developers should consider whether their proposed solutions are generalisable for different contexts, and whether they are able to increase in scale alongside the healthcare services [204]. AI tools should be validated in dynamic scenarios and different data sources, have continuous performance monitoring, and mechanisms for model updating to ensure reliability over time.

Bias and fairness: AI-driven demand and capacity models have the potential to influence resource allocation decisions at scale, thereby amplifying both positive and negative effects across patient populations. It is expected that AI models reflect the biases existing in the data used used in training, such as lack of representation of minority demographics. Therefore, AI tool developers should be aware of such biases and take steps to address them to promote fairness in the recommendations made by the automated tools. Addressing these risks requires explicit evaluation of model performance across demographic subgroups (incorporating data-level interventions such as reweighing under-represented groups and synthetic data generation), the incorporation of fairness-aware learning strategies, and transparent reporting of limitations [2].

Hospital Policy Adjustments and Seasonal Variations: In some hospitals, during peak seasons (e.g. flu season) or specific periods (such as holidays or fiscal year-end), internal guidelines such as admission/readmission thresholds may be adjusted [5]. An additional challenge concerns the robustness of AI-based forecasting models during crisis events, such as pandemics, supply chain disruptions, workforce shortages, or sudden surges in demand. These shifts change the underlying data distribution the AI models depend on. Consequently, AI models should be trained using all relevant data (i.e., retraining a model after a policy change, or training different models for different seasons), in order AI predictions to be reliable in different scenarios.

Data Interoperability and Infrastructure: One challenge in implementing AI tools within healthcare is the fragmented nature of data storage and management. Several hospitals rely on a variety of database systems that do not communicate seamlessly, making it difficult to gather complete patient information or conduct real-time analyses. AI models may underperform or offer incomplete insights because they lack access to all relevant data, so effort in collection and preparation of data is required, to ensure that the datasets used to train models are clean, relevant and sufficient. Additionally, many state-of-the-art approaches, particularly deep learning and large ensemble models, require substantial computing resources, specialised hardware, and dedicated data engineering pipelines. These requirements may pose barriers for healthcare providers operating within constrained budgets or relying on legacy IT infrastructures. These constraints highlight the importance of considering computational efficiency, robustness, and ease of integration when designing AI tools for healthcare systems management.

Standardization of processes and evaluation metrics: It is required for fair comparisons and easier interfacing between different methods [4]. AI applications in healthcare data should use data that comply with privacy and quality standards, generate fair and interpretable predictions and insights, and are standardized to integrate with existing systems and be comparable to other methods.

IV. CONCLUSION

This review explored the use of artificial intelligence in demand and capacity modelling in healthcare systems, with a focus on how AI methods are being used to support operational or planning decision-making. By systematically analysing studies across demand prediction tasks (e.g. prediction of admissions, readmissions, length of stay) and capacity planning problems (e.g. prediction of beds and workforce requirements) the review provides a consolidated view of current methodological practices and application areas. The findings indicate several developed approaches in demand modelling based on supervised machine learning approaches, with tree-based and deep learning models being popular, while in capacity modelling although machine learning approaches have also been used less studies have found and often relies on narrower problem formulations or traditional statistical techniques.

The insights provided by AI-based tools can be used in decision support by experts. However, trust in these insights is strongly dependent on the interpretability of the models and their predictions, which indicates a need for focusing on explainable AI for problems related to healthcare systems management. Furthermore, XAI applications facilitate transparency concerns such as ensuring ethics standards, properly handling sensitive data, and providing insights that are actionable for policymakers and healthcare providers. Despite promising results reported across many studies, significant challenges persist, including limited generalisability, inconsistent evaluation practices, data interoperability constraints, and risks related to bias, fairness, and ethical deployment. Overall, the evidence suggests that AI-based demand and capacity models have substantial potential to enhance healthcare systems management, but real-world impact will depend on closer integration between demand and capacity modelling, stronger emphasis on transparency and robustness.

APPENDIX

Figure 2 illustrates the PRISMA diagram of the process followed to literature identification, screening, eligibility assessment, and inclusion in this review article. The keywords used on the search databases (IEEE Xplore and Google Scholar) for screening of relevant papers were AI/ML together with each category of healthcare systems management. The inclusion and exclusion criteria are described in the PRISMA diagram.

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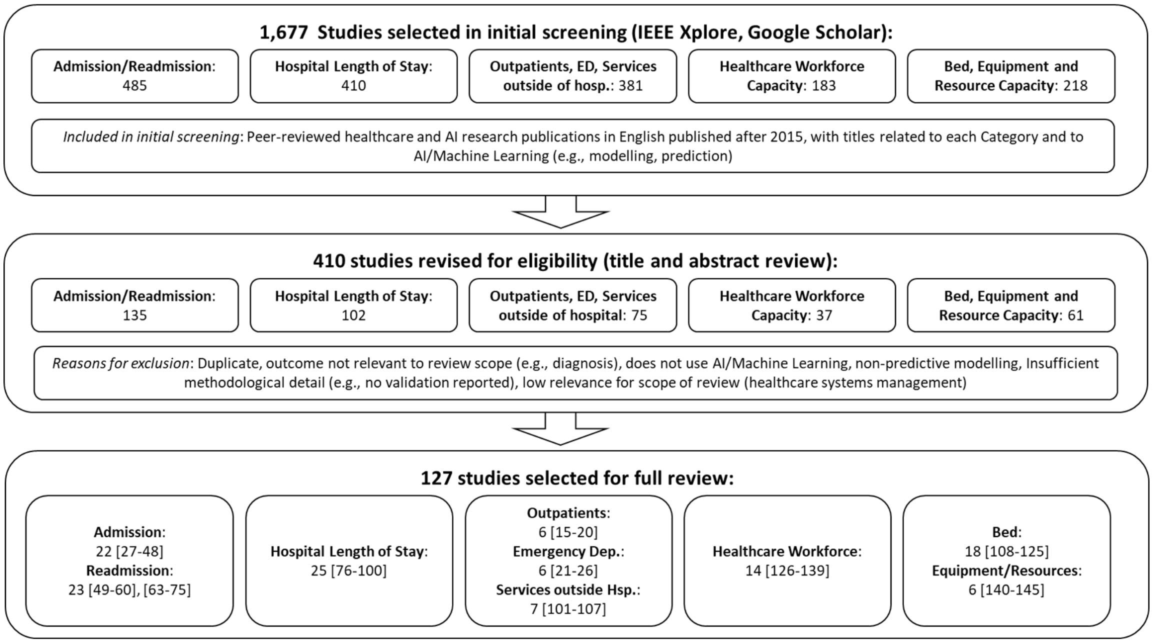

Fig. 2: PRISMA diagram illustrating the review process.

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