International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 11 Issue 08, August-2022

A Broad Analysis of Computational and AI Algorithms for Optimizing Hospital Management

Ishan Vatsaraj
Department of Biomedical Engineering
Vidyalankar Institute of Technology
Mumbai, India

Dr. Jitendra Toravi
Department of Biomedical Engineering
Vidyalankar Institute of Technology
Mumbai, India

***Abstract*— With the ever-increasing world population, the demand for healthcare services and hospitals, in general, is increasing. The number of patients visiting hospitals is growing exponentially, putting a strain on hospital administration and management. Optimizing workflows in hospitals is necessary for an efficient flow of patients and optimal resource management in the hospital. This paper comprehensively studies the computational techniques based on Machine Learning and Artificial Intelligence for optimizing hospital management. Artificial Intelligence and machine learning techniques are used in Hospital Management in many ways, from the admission of a patient to predicting the days after which a patient might get readmitted. In addition to these predictions, AI techniques increase the efficiency of various hospital processes, optimize the workflows and pathways in the hospital, and provide support for improving Healthcare Logistics.**

Keywords—Hospital Management, Artificial Intelligence, Machine Learning, Optimization

I. INTRODUCTION

We live in the Age of Information, evident from the exponential use of information and data in healthcare. In the last century, a doctor who recently graduated would probably use the medical information learned in college without any tangible increase in knowledge or information. Fifty years later - today, they have to address a gap in knowledge obtained in college and used in the field. Today, new information and disruptive techniques are introduced rapidly. Education Institutions must keep pace with these changing horizons. Data Science principles must be utilized to face this deluge of information. Artificial Intelligence (AI) helps us harness this power and intelligence obtained from this healthcare. AI augments human care and helps us to use it to do good. AI is and will be used to keep people in good health and provide the necessary care.

The world population is increasing day by day. Many countries in the world have rapidly aging populations. Many older adults will have to be cared for and treated for various ailments in the next few years. There is also an acute shortage of trained medical staff due to a lack of motivation and high attrition rates. Under these challenging circumstances, the ability to succeed humanely will only depend on automation and digitization. AI can deliver critical results for meeting the desired quality standards.

This management and implementation of new technological solutions require that qualified and trained people from IT, engineering, and robotics work together with medical professionals. Managers executing services in clinics, home care, and hospitals must become more proficient in technology. Most technologies can provide benefits in a multitude of applications [1][2][3].

In the first quarter of 2021, Global digital health funding jumped by 9%, and Global healthcare funding hit a new quarterly record [4]. In the second quarter, Global healthcare investment rose for the seventh consecutive quarter exceeding $34.7B across nearly 1600 deals [5].

AI in medicine presents virtual solutions and those which are physical.[6] The virtual solutions are exemplified as electronic health record (EHR)systems to Machine Learning (ML) based guidance in the decision for treatments powered by Artificial Intelligence (AI). The physical part deals with robot-assisted surgery, intelligent prostheses, and geriatric care. The foundations of evidence-based medicine are to establish clinical correlations and develop insights by discovering associations and patterns from an existing dataset of information. In the early years of automation, statistical methods established patterns and associations. Machines - notably computers- learn to diagnose a patient by flowcharting the information or analyzing a dataset/s. The flowchart-based approach will involve merely translating the inquiry process, i.e., a physician asking a series of questions (history-taking) and then arriving at a diagnosis - with a certain probability, by combining and co-relating the symptoms thus presented. If we have to consider the wide range of symptoms and disease processes in day-to-day medical practice, a large amount of data must be analyzed. This analysis requires machine-based cloud networks. Furthermore, the outcomes of this approach are limited because machines cannot observe and gather cues that a doctor can only observe during the patient visit and a check-up. On the contrary, analyzing a dataset using principles of deep learning or pattern recognition is better suited. These involve teaching a computer by ML algorithms that repetitively apply a process, recognizing with fantastic accuracy what certain groups of symptoms mean, and successfully diagnosing diseases using the patient's symptoms [7]. With the help of computer vision and image processing techniques, ML algorithms can recognize and classify clinical/radiological images and detect anomalies that the physician can further analyze and treat [8].

There are hundreds of papers elucidating techniques of machine learning (ML) and artificial intelligence (AI) [9]. We will try to unravel a few artificial intelligence capabilities in healthcare logistics, operations research, and other areas. [10]. We explore around 30 papers on AI in Hospital Management to reveal existing research and explore some future possibilities.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 11 Issue 08, August-2022

This work is broadly structured as follows: Section II mentions the motivation behind this study. In section III, various techniques used in Artificial Intelligence are described. Section IV describes the broad classification of AI Applications in Hospital Management. Challenges faced in Artificial Intelligence are mentioned in section V. An exhaustive literature review is described in section VI. Section VII outlines the other applications of AI in hospital management and recommendations. Lastly, section VIII highlights the conclusion of this work and its future scope.

II. MOTIVATION BEHIND THIS STUDY

The demand for efficient healthcare services in India is increasing, especially in public and government hospitals. Long patient queues, long waiting hours, improper medical records, and missing medical history are some of the leading causes of improper and inefficient diagnosis. After proper diagnosis, due to the large population, radiological screening, surgical procedures, and other operation requirements need efficient scheduling and optimization. The cost of this process also increases accordingly. Thus, we would add our bit to the body of knowledge by providing a holistic overview of AI in healthcare logistics. We will attempt to highlight priorities in future research in this field which is likely to bring industry-wide changes to the healthcare field. This study aims to provide a comprehensive summary of the current techniques used in hospitals. It also highlights proposed techniques for optimizing hospital management worldwide for efficient diagnosis, optimal patient flow, and surgery scheduling while mitigating the problem of insufficient hospital beds by automated allocation and many others.

III. ARTIFICIAL INTELLIGENCE

The ability of a machine to perform tasks that require human-level intelligence is called AI. AI systems perform non-algorithmic processing, i.e., the functions performed by a knowledge-based AI system depend on its use case. AI programs can learn, i.e., the systems improve with new data over time. Artificial Intelligence comprises many techniques like Machine Learning, Deep Learning, Natural Language Processing, Computer Vision, and other techniques.

A. Machine Learning

Machine Learning Algorithms iteratively learn from problem-specific training data, which allows computers to find hidden insights and complex patterns without explicitly being programmed. Learning from previous computations and extracting regularities from massive databases can help produce reliable and repeatable decisions. The three categories of ML are supervised learning, unsupervised learning, and reinforcement learning [11].

B. Deep Learning

Deep Learning (DL) consists of neural networks with more than one hidden layer organized in deeply nested network architectures. DL is beneficial in domains with high-dimensional data. Deep neural networks outperform shallow ML algorithms for most applications in which text, image, video, speech, and audio data need to be processed [11].

C. Natural Language Processing

Natural Language Processing algorithms interpret the parts of speech and the meaning of a sentence and then convert the sentence/commands into the computer’s language that it can understand and process. Such algorithms transform sentences occurring as part of a dialog into data structures that convey the intended meaning of the sentences [12].

D. Computer Vision

Computer vision algorithms enable systems to see, identify and understand the visual world, simulating the same way human vision does. Algorithms for visual perception tasks include (i) object detection in order to localize instances of semantic objects of a given class, (ii) object recognition in order to determine whether image data contains a specific object, and (iii) segmentation for scene understanding to parse an image into meaningful segments for analysis [13].

IV. AI IN HOSPITAL MANAGEMENT

Increasing the Process Efficiency of Hospitals can be classified broadly into these categories [14]:

A. Access to Care

This category includes admission of a patient, scheduling of patient appointments, and other patient services. Using Big Data to autofill the patient's demographic details increases the speed of the patient admission process. Digitizing patient records help access other details like the patient history. These modifications can help improve the admission process of the patient by finding the most suitable hospital based on location, level of emergency, and other medical histories of the patient. For patient appointment scheduling, AI can be used to predict patient wait time based on the patient's diagnosis. Intelligent scheduling of patients is possible by incorporating the time of arrival to the center based on the patient's live location and emergency level resulting in reduced delays in appointments.

B. Delivery of Care

This category includes optimal resource management and forecasting using AI. Some use-cases in hospitals are: predicting bed availability, predicting staff requirement, predicting patient discharge, scheduling diagnostic services, and forecasting the resource requirement and volume of patients arriving in the emergency department based on historical data.

C. Accounting for Care

This category includes managing the financial transactions in the hospital by analyzing bills and invoices, detecting anomalies in the hospital bills, accounting for the cost of forecasted resources, optimizing the hospital's revenue cycle, and predicting insurance claim denials.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 11 Issue 08, August-2022

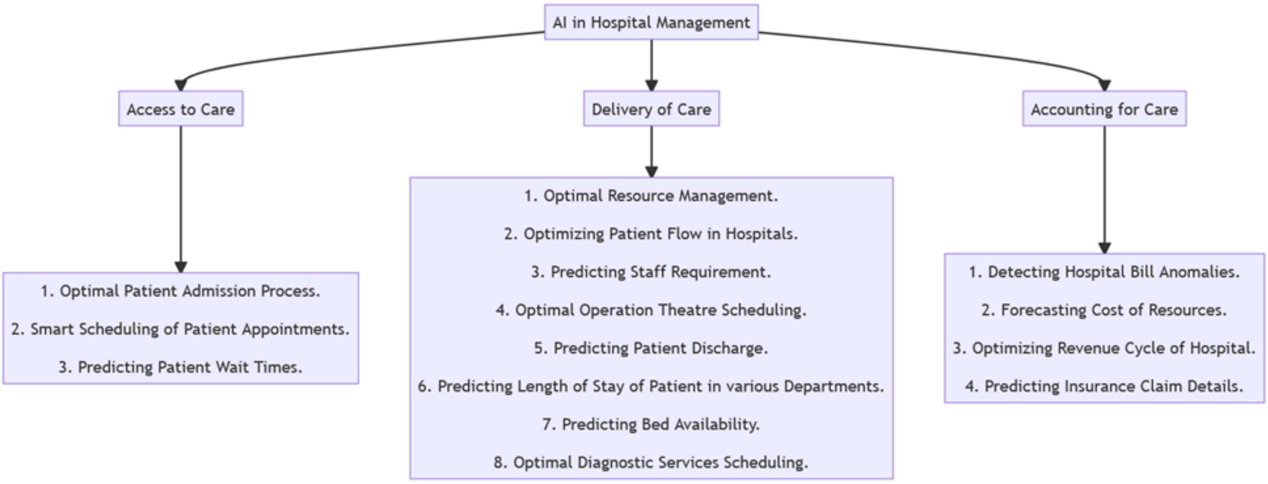

Fig. 1. Classification of Works with respect to care

V. AI CHALLENGES

Machine learning methods offer great promise for fast and accurate detection and prognostication of COVID-19 from chest radiographs (CXR) and HR-CT images. Driggs et al. [15] found that out of 2,112 models, none could be used in potential clinical scenarios, and it was discovered that most of them had methodological flaws or underlying biases.

There are also ethical implications around the use of AI in healthcare. In the past, when AI systems were not used, all healthcare decisions were made exclusively by trained and qualified doctors; thus, using AI-assisted devices to assist or make decisions for them automatically raises privacy, permission, accountability, and transparency. The most contentious issue among them is transparency. Many Deep learning algorithms used for image analysis are complicated and impossible to interpret or explain to a non-specialist. Patients need to know the why and how of morbid diagnoses - like cancer. Physicians who are generally familiar with their operation may also be unable to provide an explanation of the diagnosis in this case. ML systems in healthcare, like all ML systems, are subject to algorithmic bias and may predict a greater likelihood of disease based on factors like gender or race when they may not be causal. Who would be accountable when an AI system mistakes patient diagnosis and treatment? A clinician would be more suited to provide information in certain situations in a more empathetic way than a machine that might hurt the patient or loved ones by simply stating the details. For those reasons and more, it is imperative that healthcare institutions, governments, and regulatory bodies, establish structures and monitor critical issues, react responsibly and establish mechanisms to limit negative implications as ML and AI are the most powerful and consequential technologies to impact human society in the 21st century. It requires continuous attention and astute policy making for many years [16].

There is a big challenge before us to translate the available AI research, in a safe and timely manner, into clinically validated and appropriately regulated systems that benefit everyone. Clinical evaluation using robust metrics intuitive to doctors should be performed on all research. They should include quality of care and patient outcomes as metrics in addition to the usual measures of technical accuracy. Themes of algorithmic bias and unfairness while developing mitigations have to be addressed, brittleness has to be removed, generalizability has to be enhanced, and methods for improved interpretability of machine learning predictions have to be developed [17].

In principle, machine learning in healthcare uses observational data, which are not reasonably accurate in answering causal queries. Using Simpson's Paradox, the relationship between two variables is affected by adding more relevant data. This is illustrated by prior work [18], in which the subpopulation mortality rate of asthmatic patients admitted to hospitals was lowered when they were treated for pneumonia.

A significant amount of work remains to be done in the retraining of models and validating results obtained. This is despite the conspicuousness of machine learning in modern medicine. Researchers are finding newer algorithms and data analysis methods that mimic the most experienced clinical personnel in diagnosis and analysis. Hospitals attached to Medical Colleges can shed significant light on this area as they can encourage transdisciplinary research through the exchange of information concerning the application of machine learning in a clinical setting [19].

Thomas Davenport and Julia Kirby, in their work [20], suggested the following ways institutions can respond to AI. Institutions could step up by upskilling and adapting, step aside by developing strengths that are not codifiable cognition, and step in by volunteering to modify and monitor software. Institutions could also step forward by building the next generation of technology, step narrowly by specializing in medical tasks where computers are useless. In the worst-case scenario, financial and cultural pressures may drive clinicians to step narrowly to specialize in a way they can avoid technology altogether. A best-case scenario can be achieved by allowing clinicians to undergo informatics and statistics training; they may step in to modify and monitor current software. However, clinicians who want to step forward must depend on health system leaders who have to invest in programs that allow them to develop new technologies that shape the future.

VI. LITERATURE REVIEW

In this section, different techniques for optimizing processes in Hospital Management using Artificial Intelligence are discussed:

A. Access to Care

a) Outpatient Department:

Bu et al. [21] developed an Outpatient Triage System based on Dynamic Uncertainty Based Causality Graph (DUCG). This system is developed to aid the triage nurses in achieving the outpatient triage accurately. This hybrid DUCG system combines the single-valued DUCG (S-DUCG) and multivalued DUCG (M-DUCG) systems. The knowledge base required for the outpatient triage system is developed by considering each department in a hospital as a sub-DUCG and compiling all the sub-DUCGs to make one complete DUCG. The fundamental outpatient triage base is developed using the M-DUCG. S-DUCG is used to make this system scalable and to adjust this system to meet the requirements of various hospitals. The knowledge base has 436 clinical features related to 31 different departments. The overall accuracy of the developed system was 97.8%.

Safdar et al. [22] developed a Data-Driven Scheduling Algorithm (DDSA) to generate a Physician Visiting Schedule for a Better Patient Experience. The system applies different set-up times to allow hospital management to trade between doctor and patient waiting times. This algorithm works in three steps – Distribution, Clustering, and Doctor Scheduling. The DDSA distributes the patients into four categories – Report Showing, Follow Up, New Patient, and Serious Patient. It assigns each patient a cluster head time for the treatment, and different patient categories are assigned different treatment times. Lastly, the patient and doctor commutative wait times are calculated. The average wait time after implementing DDSA is about seven minutes.

Safdar et al. [23] also developed an Outpatient Experience Management System using RFID, sensors, and a Genetic Algorithm. The time-related information of each patient collected from RFID, Patient experience from survey applications, data from sensors, and HMIS are included in the dataset. The system's accuracy is about 80.3%, and the average error is 0.322.

Cho et al. [24] developed an Evidence-Based Decision Support Framework for Clinician Medical Scheduling. This system also reduces the patients' waiting time. The developed system is based on real-world data from the EHR system of a fully digitalized tertiary general university hospital in Korea. The system reduced the waiting time for consultation by at least 2.84% (scenario 4) and up to 55.20% (scenario 1).

Li et al. [25] proposed an AI system to reduce outpatient waiting time. In this system, AI has been used in two places. Once the patient registers, an AI bot collects and analyzes the medical history of the patient and sends it to the AI doctor. This AI doctor acts as a real-world doctor and asks questions based on the patient's illness. After concluding, the bot recommends basic diagnostic tests which a doctor would recommend. These test results are sent to the doctor, and further diagnosis and treatment proceed like the conventional procedure. This study verified that taking a laboratory or imaging test before consulting the doctor reduces the patients' wait time significantly and speeds up the diagnosis and treatment process. It also reduces the amount spent by the patients.

Simini et al. [26] proposed two AI systems, one to automate the chronic follow-up process, namely SIMIC, and the other to assist the outpatient diagnosis, PRAXIS. SIMIC is an application prescribed by a doctor to a patient. It interacts with the patient daily, monitoring the patient's vital parameters. Once the patient is diagnosed with a particular disease, the app parameters are modified accordingly. If the patient's parameters are out of the pre-established limits, suggestions are given to the patient for follow-ups, and an alert is sent to the healthcare team. In this way, it helps prevent losses to follow-up and gives opportunities to the healthcare team to intervene before rehospitalization is mandatory or when facing an emotional emergency. PRAXIS is an AI application that remembers the details of all the previously diagnosed cases and helps the doctor by providing necessary details during a patient's diagnosis.

b) Emergency Department:

Bruballa et al. [27] developed an Agent-based Model (ABM) system for intelligent scheduling of Non-critical Patients' Admission to the Emergency Department. The authors designed an analytical model to calculate the response to the capacity of a particular healthcare staff configuration in an ED.

El-Bouri et al. [28] developed a deep-learning-based system for predicting Hospital Admission Location. This system predicts where the patients triaged in the emergency department will be admitted, helping allocate beds and resources for optimal care of patients. The dataset in this study containing about 9324 patient data was collected from the Electronic Health Records from the Oxford University Hospitals between January 2013 and April 2017. The system is validated using the MIMIC-III dataset. The algorithm uses a curriculum learning-based approach, with the regularization achieved using Mahalanobis Curriculum. A multi-armed bandit approach is used to choose the most optimal batch for training the network. The algorithm classifies the patient in one of the seven wards – medical, cardiac, neurology, trauma, ICU, surgical, and general & gynecology. For individual ward types, the model achieves AUC values between 0.60 and 0.78.

Sharafat et al. [29] proposed a deep-learning-based approach for predicting patient flow in emergency departments – PatientFlowNet. The dataset used in this paper is based on the data collected from the Emergency Departments of three hospitals in New York City. The model considers two types of variables – exogenous and endogenous. Exogenous variables are those the system does not have any control over, i.e., patient arrival time. In contrast, variables like treatment and discharge time are controlled by the system and are hence categorized as endogenous. This model has a mean absolute error of less than 4.8%.

Jin et al. [30] developed a system to predict emergency medical service demand using Bipartite Graph Convolutional Networks. This study uses ambulance data containing 624,062 emergency cases, and the data is collected from 1st January 2017 to 31st December 2017 in the Central Tokyo area. This system achieves 77.3% − 87.7% accuracy in binary demand label prediction tasks.

Allihaibi et al. [31] developed a stochastic Emergency Department Simulation-Optimization Approach to solve the emergency care patient pathway. Stochastic variables like patient interarrival times and treatment times which depend on day shifts and patient categories, are considered in this approach. Furthermore, the authors also integrated a hybrid evolutionary algorithm to find a satisfactory solution to this optimization problem in real time. This algorithm achieved an overall improvement of 10.4% in patients' waiting time.

Graham et al. [32] developed and compared three machine learning models based on data mining for predicting hospital admissions from the emergency department. This work used administrative data from two major acute hospitals in Northern Ireland. The authors used machine learning algorithms like Logistic Regression, Decision Trees, and Gradient Boosted Machine. The maximum accuracy obtained was 80.31%. The authors also identified several factors related to hospital admissions like hospital site, age, arrival mode, triage category, care group, previous admission in the past month, and last admission in the past year. Practical implementation of these models can be used as a decision support system to optimally manage the patient flow from the emergency department to hospitals.

Kim et al. [33] designed and developed a machine learning-based hospitalization predictive model for predicting hospitalizations of patients in the emergency department. The data used in this study was based on data recorded in the electronic system of Korea University Anam Hospital (KUAH), a general hospital in South Korea. The data includes about 28000 patient records for seven months from October 2018 to April 2019. The developed model achieved an accuracy of about 89%.

B. *Delivery of Care:*

a) Operation Theatre / Surgery Scheduling:

Wang et al. [34] proposed a system based on Column Generation for Integrating Surgeon and Surgery Scheduling. The patient-preference-driven approach identifies an effective solution to operating room scheduling, and this solution satisfies patients' preferences with only slightly increased staffing costs. The performance of the column generation-based heuristic algorithm is tested on different scale instances. Additionally, this algorithm obtains solutions within a 1.6% gap of the lower bound obtained by the linear-relaxed problem.

Luo et al. [35] developed a block allocation method for Two-Stage Operating Room Scheduling. In the first stage, the algorithm allocates the patients to blocks, and the date of each block is undetermined. An Integer Programming (IP) model helps achieve the balanced allocation of each surgeon's block and is used to obtain the result of each block composition. Next, the second stage assigns blocks and helps in surgery sequencing. The operation date of each surgical block is obtained through the other IP model based on the first stage. The goal of the second stage is to minimize the waiting cost for patients. Patients are sorted in each block according to the surgical type and priority.

The system proposed by Ripon et al. [36] deals with the different uncertainties that can occur during the surgery and how it affects the scheduling of the following surgeries. Hospital surgery scheduling is a very detailed and precise process, and it starts with the patient getting appointed for surgery and ends with the completion of surgery. It involves many micro-tasks like scheduling an appointment with the surgeon, obtaining and arranging resources for the surgery, scheduling and appointing operating rooms with special diagnostic equipment, deciding the time of surgery based on the type of patient (inpatient or outpatient), and finally the time interval of the surgery. There are two sources of uncertainty in this process: arrival uncertainty (time of arrival of patient/staff for surgery) and duration uncertainty (time duration of surgery based on activities performed before, during, and after the surgery). Conceptual visualization of the problem can be found in the following image. The authors of this paper use Genetic and Evolutionary computing algorithms to address this problem. However, machine learning algorithms can also be applied to tackle the problem of acquiring appropriate data.

Saleh et al. [37] proposed a system that allocates Operating Theatre time for each specialty in a multispecialty hospital. Here, the problem is the overlap of shifts, overtime of staff, inefficient use of resources, and other problems. The authors propose a block scheduling technique for equitable allocation of time among surgeon groups in hospitals with limited time capacity in the operating room. This block scheduling technique is based on the experience and expertise of surgeon groups or the formulas based on overall performance optimization from the partial margins' contribution of these surgical teams. The proposed model's utilization rate (adequate work time allocated/maximum capacity in hours) is 78.3%. Also, there is no overlap of shifts, and the two specialized ORs provide the surgery team they are qualified to serve.

b) Hospital Resource Management:

Liu et al. [38] proposed a GRA-based method for evaluating medical service quality. In the proposed system, the Delphi method determines criteria and establishes an evaluation system by 23 experts. Then, the quantification of the current uncertainty and ambiguity is achieved by the interval-valued intuitionistic trapezoidal fuzzy numbers (IITFN). Criteria Weights are determined, and alternatives are evaluated by aggregating the subjective and objective information using the Grey Relational Analysis (GRA) Method.

Mora Garcia et al. [39] proposed a tool to provide an additional criterion for making decisions about the replacement priority of the medical equipment, the sensible investment of the financial resource, and, where appropriate, the acquisition of new medical equipment. The authors consider three variables for each piece of equipment: Technical (availability of spare parts in the next five years, age of equipment, equipment failure frequency), Clinical (daily use of equipment in hours, out-of-service equipment hours), Economic (Purchase Cost, Maintenance cost, useful lifetime). Partial indicators depicting variable relevance were calculated and mathematically modeled. Finally, evaluation was done by incorporating these partial indicators and modeling them to predict the replacement priority.

Lu et al. [40] proposed a model for optimal allocation of Cashiers and Pharmacists in Large Hospitals. A point-wise fluid-based approximation approach is adopted to construct a dynamic queuing network that considers patients' time-varying (or non-stationary) arrivals and describes time-varying queue lengths. The dynamic queuing network is then encapsulated in the optimization model that determines the optimal time-varying numbers of cashiers and pharmacists. In the results, the Taipei hospital can save about 15% of its operating cost and decrease 91.6% of the waiting cost per day.

c) Optimization of Processes in Hospital:

Z. M. Ibrahim et al. [41] developed a knowledge distillation ensemble framework for predicting Hospitalization outcomes from Electronic Health Records (EHR). The dataset used in this study is a combination of three datasets: COVID-19 General Ward Data, Pneumonia ICU Data, and CKD ICU Data. The architecture of the proposed model is divided into two modules. The first module is designed to use the data's dynamic view. The Dynamic-KD consists of an unsupervised LSTM Autoencoder model, which is self-trained on a subset of outcomes. The second module Static-OP is a classification ensemble based on gradient boost trees. This module aims to complement the predictions made from dynamic data by Dynamic-KD. The model achieved an average Precision-Recall Areas Under the Curve (PR-AUCs) of 0.891 (95% CI: 0.878-0.939) for mortality and 0.908 (95% CI: 0.870-0.935) in predicting ICU admission and readmission.

Alshwaheen et al. [42] proposed a deep learning framework to predict the deterioration of patients in ICU. The proposed model is based on LSTM-RNN and is optimized using a GA-based multi-objective optimization algorithm. The data used in this study is collected from the MIMIC-III dataset. The model is evaluated based on two tasks, i.e., mortality and sudden transfer of patients to ICU. The model predicts the deterioration one hour prior to the onset. The model achieved an accuracy of 92.1% and an AUCROC of 0.933.

Wu et al. [43] proposed a deep-learning-based model for predicting adverse events in adult hospitalized patients. The adverse event prediction is performed on the physiological data (vital signs) from the last 28 hours of an adverse event. The dataset used in this paper is collected from the hospital electronic medical record data warehouse (2007 - 2017). This study shows that Convolutional Neural Network with class balancing and aligning by hour gets the best results. The precision, recall, and area under the curve obtained by the model are 0.841, 0.928, and 0.995, respectively.

Ippoliti et al. [44] proposed an ANN-based model to predict hospital patients' length of stay (LoS). The data used in this study was collected from the Department of Internal and Emergency Medicine (DIEM) of a general hospital in the North-West of Italy. The data contained information on more than 16,000 hospitalizations across 13 different departments between January 2018 and December 2019. The model indicated that the management of DIEM could reduce the average LoS by up to 2 days resulting in more than 2000 additional hospitalizations per year.

The system proposed by Cuadrado et al. [45] uses machine learning algorithms to predict the time (in days) it takes for a patient to get discharged after getting admitted to ICU. Predicting days to discharge is a complex problem involving many variables like the patient's critical condition, possible unexpected complications, interventions of different specialist doctors, and other variables. However, the authors have developed the prediction model based on factors like the clinical values of patients being recorded daily, heterogeneity between patients, i.e., diversity in a group of patients getting discharged during the same period, and similarity between them and their phenotypes. Towards the end of the paper, the authors suggest using time series analysis for better prediction.

Munavalli et al. [46] proposed a hospital model as a multi-agent system for optimizing patient flow and hospital capacity management. The different agents in this work are the patient agent, resource agent, department agent, route agent, patient schedular agent, and resource schedular agent. The patient agent tracks patient movements in the department according to clinical pathways. The resource agent maximizes the utilization of hospital staff, and the department agent keeps track of all patients and resources in the department. The route agent assesses the waiting time in each department; the patient schedular agent creates a route agent for finding the optimal path for patient agents. The resource schedular agent overlooks everything in every department. With this agent, the hospital can utilize its system for scheduling patients and resources.

Mellouli et al. [47] studied and presented opportunities for adequate hospital-wide decision support with the collaboration of AI and Operations Research. This study describes where AI and OR can be synergized for optimal patient flow and hospital-wide decision support. A patient-centered clinical pathway is also discussed, and its benefits using real-world case studies are shown.

Jiang et al. [48] proposed and designed hybrid models of Time Series Regression and Deep Neural Networks. These models are used for forecasting patient flows in Hong Kong. Time-series data of patient arrival volume from July 1, 2009, through June 30, 2011, in a Hong Kong A&ED center was collected to test these hybrid models. Compared to Zhang's method, the moving average filter-based method and Khashei's method achieve lower MAPE among the proposed strategies.

Huang et al. [49] proposed a machine-learning-based framework to mine the hidden medication patterns in EMR text. The authors analyzed actual EMR text from a major hospital in China, consisting of 998 inpatient EMRs from June 2014 to July 2016. Medication patterns from EMRs, for diseases with minor treatment variances from complex medication treatments, were effectively identified in this study.

C. *Accounting for Care:*

Zeng et al. [50] proposed a multi-view deep learning framework for predicting patient expenditure in healthcare. The data used in this study is based on administrative claims data collected from the Medicaid program by Partner for Kids (PFK). The dataset contains more than 8,500,000 medical records of 450,000 patients from Jan 2013 to Dec 2014. The models used in this study include a feedforward neural network, an attention-based bidirectional recurrent neural network, and a hierarchical attention network to exploit heterogeneous information in claims data from different views.

TABLE I. PUBLISHED WORKS OF AI IN HOSPITAL MANAGEMENT

Authors	**Year of Publication**	**Hospital Department**	**Problem Tackled**	**Classification**	**Approach/Algorithm**
Bu et al.	2020	Outpatient Department	Outpatient Triage	Access to Care	Dynamic Uncertainty Based Causality Graph
Safdar et al.	2021	Outpatient Department	Physician Visiting Schedule for Better Patient Experience	Access to Care	Data Driven Scheduling Algorithm (DDSA)
Safdar et al.	2020	Outpatient Department	Outpatient Experience Management	Access to Care	Outpatient Experience Management System using RFID, sensors and Genetic Algorithm
Cho et al.	2019	Outpatient Department	Reduce the waiting time of the patients	Access to Care	Evidence-Based Decision Support Framework for Clinician Medical Scheduling
Li et al.	2021	Outpatient Department	Reduce outpatient waiting time	Access to Care	XIAO YI
Simini et al.	2020	Outpatient Department	Automate the chronic follow-up process, assist the outpatient diagnosis	Access to Care	SIMIC, PRAXIS
Bruballa et al.	2019	Emergency Department	Intelligent scheduling of Non-critical Patients Admission	Access to Care	Agent based Model (ABM)
El-Bouri et al.	2020	Emergency Department	Predicting Hospital Admission Location	Access to Care	deep-learning based system
Sharafat et al.	2021	Emergency Department	Patient flow in emergency departments	Access to Care	PatientFlowNet
Jin et al.	2021	Emergency Department	Predict emergency medical service demand	Access to Care	Bipartite Graph Convolutional Networks
Allihaibi et al.	2021	Emergency Department	Solve the emergency care patient pathway	Access to Care	Simulation-Optimization Approach
Graham et al.	2018	Emergency Department	Predicting hospital admissions from the emergency department	Access to Care	Machine Learning Algorithms
Kim et al.	2022	Emergency Department	Predicting hospitalizations of patients in ED’s	Access to Care	Machine Learning based Hospitalization Predictive Model
Wang et al.	2018	Operation Theatre	Surgeon and Surgery Scheduling	Delivery of Care	Column Generation Approach

Luo et al.	2019	Operation Theatre	Two-Stage Operating Room Scheduling	Delivery of Care	Block Allocation method
Ripon et al.	2019	Operation Theatre	Different uncertainties which can take place during the surgery and how it affects the scheduling of the following surgeries	Delivery of Care	Genetic and Evolutionary computing algorithms
Saleh et al.	2021	Operation Theatre	Allocation of Operating Theatre time for each specialty in a multispecialty hospital	Delivery of Care	Block Scheduling Technique
Liu et al.	2019	Biomedical Department	Evaluating Medical Service Quality	Delivery of Care	GRA-based method
Mora Garcia et al.	2020	Biomedical Department	Decisions about the replacement priority of the medical equipment, the rational investment of the financial resource, and, where appropriate, the acquisition of new medical equipment.	Delivery of Care	Multi-Criteria Decision Analysis
Ibrahim et al.	2021	Intensive Care Unit	ICU admission and readmission	Delivery of Care	Knowledge distillation ensemble framework
Alshwaheen et al.	2020	Intensive Care Unit	predict the deterioration of patients in ICU	Delivery of Care	Deep Learning framework
Wu et al.	2021	Other	Predicting adverse events in adult hospitalized patients.	Delivery of Care	Deep-Learning based model
Ippoliti et al.	2021	Other	Predict the length of stay (LoS) of patients in hospital.	Delivery of Care	ANN-based model
Cuadrado et al.	2021	Other	Predict length of stay (LoS) of patients in ICU.	Delivery of Care	Machine Learning Algorithms
Munavalli et al.	2021	Other	Optimizing patient flow and hospital capacity management	Delivery of Care	Multi-Agent System
Mellouli et al.	2021	Other	Optimal patient flow and hospital-wide decision support.	Delivery of Care	AI
Lu et al.	2017	Other	Optimal allocation of Cashiers and Pharmacists in Large Hospitals	Delivery of Care	Dynamic Queuing Network
Jiang et al.	2019	Other	Forecasting patient flows in Hong Kong	Delivery of Care	Deep Neural Networks and Time Series Regression
Huang et al.	2019	Other	Mining the hidden medication patterns in EMR text	Delivery of Care	Machine-learning-based framework
Zeng et al.	2021	Other	Predicting patient expenditure in healthcare	Accounting for Care	Deep Learning based Approach

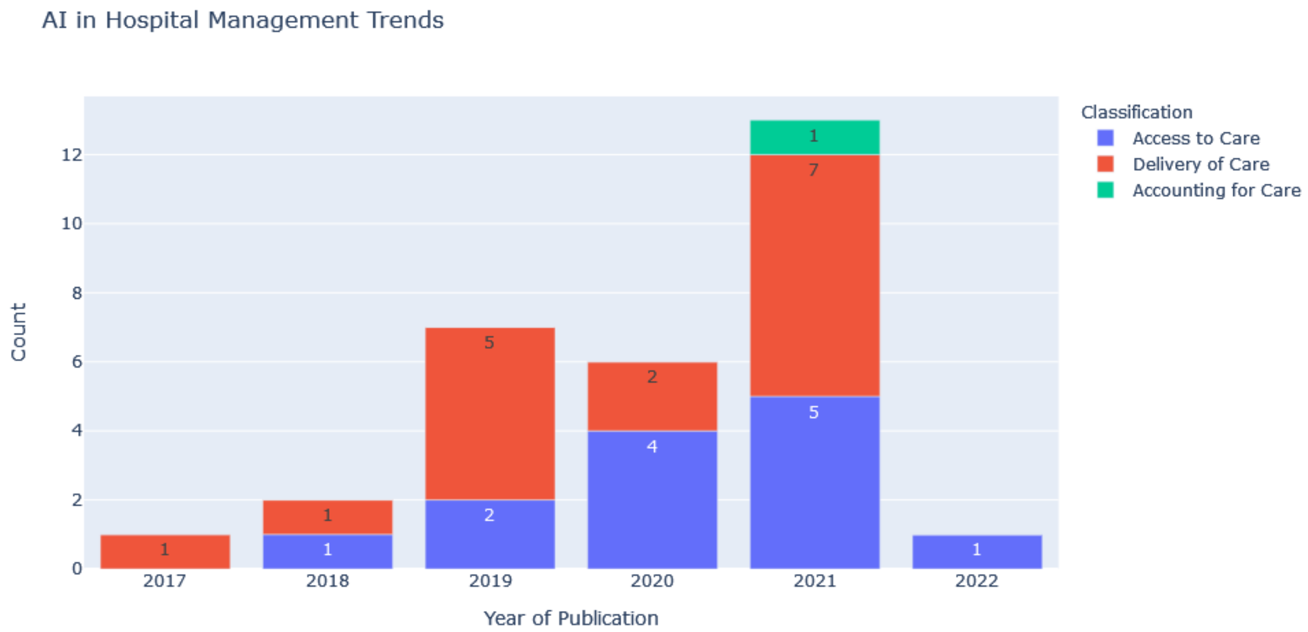

Fig. 2. AI in Hospital Management - Recent works

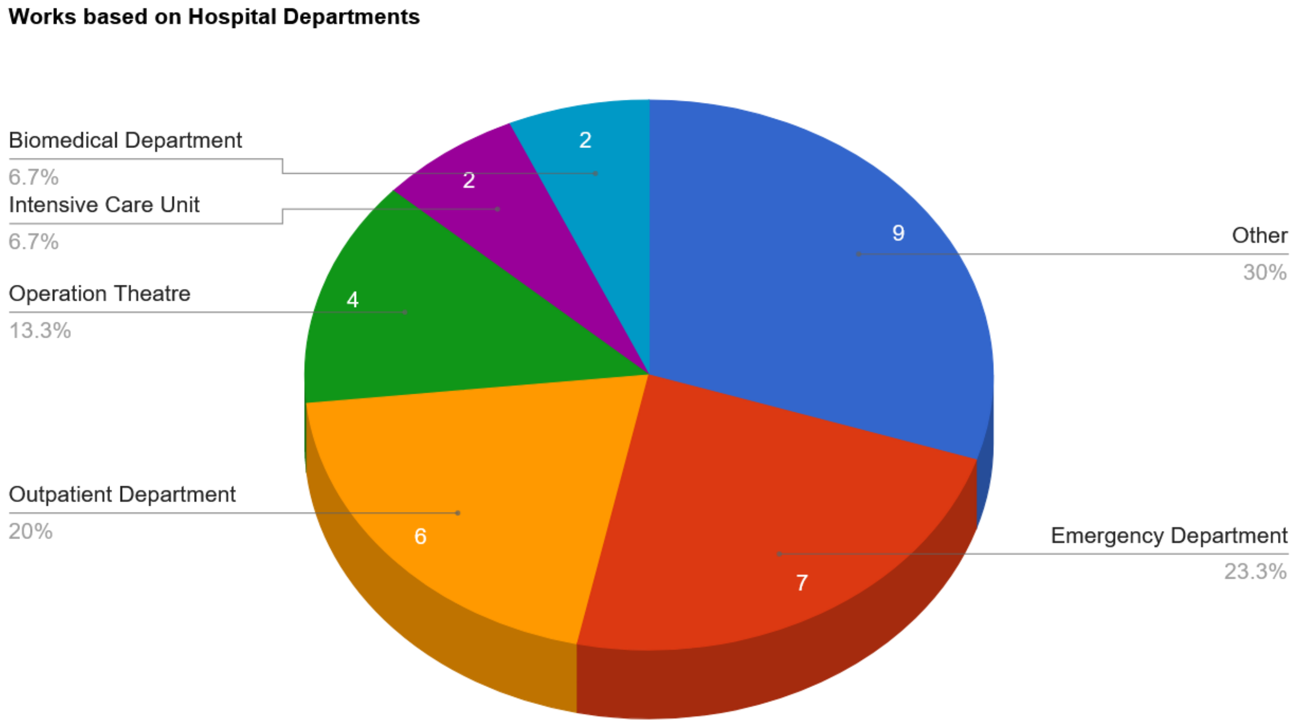

Fig. 3. Department wise comparison of Works

VII. RECOMMENDATIONS

In this study, more than 30 papers on using Artificial Intelligence to optimize workflows for efficient Hospital Management were reviewed. The reviewed works mainly focused on the outpatient department, emergency department operation theatre, and the intensive care unit. Additionally, few works focused on predicting and optimizing the overall patient flow in the hospital, adverse event predictions in hospital patients, and predicting patient length of stay in the hospital. Some other possible use-cases of AI for hospital management: Self-driving hospital beds and chairs, i.e., chairs and beds with auto-routing capabilities powered by AI can be used to reduce the number of care workers, which can result in a care worker giving more time for interaction with the patient. AI can also monitor the health of the hospital staff and private practices to check that they drink and eat enough, given their long working hours and work intensity [51].

VIII. CONCLUSION AND FUTURE SCOPE

This study has discussed various techniques and applications of computational methods and artificial intelligence in hospital management. The reviewed papers were classified based on different Hospital Departments like the Emergency Department, Outpatient Department, Operation Theatre, and other departments. They were further classified based on focus areas, i.e., Access to Care, Delivery of Care, and Accounting for Care. Good work has been done in improving "Access to Care" and "Delivery of Care." Accounting of Care is an area that requires active research. Additionally, the datasets used in the papers were focused on a particular region. Hence, the models/systems need to be trained on a larger dataset to validate the generalizability of the model/system.

Through this study, one could understand that even though these models perform very well in solving the target problem, their compatibility with available hospital information systems (HIS) needs to be tested and validated to use them on a large scale. In highly populated countries like India, there is a dire need for such a generalized and automated system. The need of the hour is a system that could combine and monitor these models—a system trained on world data, ready to be deployed and used. Efforts would be made to develop a combined system for hospitals in India to automate their workflows from patient admission to discharge, including the workflows of different departments. This study will serve as a knowledge base for future works toward developing healthcare in India.

REFERENCES

[1] Gruber, M., MacMillan, I. C., & Thompson, J. D. (2008). Look before you leap: Market opportunity identification in emerging technology firms. Management Science, 54(9), 1652–1665.

[2] Penrose, E., & Penrose, E. T. (2009). The theory of the growth of the firm. Oxford: Oxford University Press.

[3] Teece, D. J. (1982). Towards an economic theory of the multiproduct firm. Journal of Economic Behavior & Organization, 3(1), 39–63.

[4] CB Insights Research. State Of Healthcare Q1'21 Report: Investment & Sector Trends To Watch. 2021. Available from: https://www.cbinsights.com/research/report/healthcare-trends-q1-2021

[5] CB Insights Research. State Of Healthcare Q2'21 Report: Investment & Sector Trends To Watch 2021. Available from: https://www.cbinsights.com/research/report/healthcare-trends-q2-2021

[6] Pavel Hamet, Johanne Tremblay, Artificial intelligence in medicine, Metabolism, Volume 69, Supplement, 2017, Pages S36-S40, ISSN 0026-0495, https://doi.org/10.1016/j.metabol.2017.01.011.

[7] Roza Dastres, Mohsen Soori. Advances in Web-Based Decision Support Systems. International Journal of Engineering and Future Technology, CESER, 2021. ⟨hal-03367778⟩

[8] Ray Cody Mayo, Jessica Leung, Artificial intelligence and deep learning – Radiology's next frontier?, Clinical Imaging, Volume 49, 2018, Pages 87-88, ISSN 0899-7071, https://doi.org/10.1016/j.clinimag.2017.11.007.

[9] Alok Aggarwal. The current hype cycle in artificial intelligence. Retrieved from KDNuggets, 2018.

[10] Sylvain Landry and Richard Philippe. How logistics can service healthcare. In Supply Chain Forum: An International Journal, volume 5, pages 24–30. Taylor & Francis, 2004.
[11] Janiesch, C., Zschech, P. & Heinrich, K. Machine learning and deep learning. Electron Markets 31, 685–695 (2021). https://doi.org/10.1007/s12525-021-00475-2
[12] Otter DW, Medina JR, Kalita JK. A Survey of the Usages of Deep Learning for Natural Language Processing. IEEE Trans Neural Netw Learn Syst. 2021 Feb;32(2):604-624. doi: 10.1109/TNNLS.2020.2979670. Epub 2021 Feb 4. PMID: 32324570.
[13] Xin Feng, Youni Jiang, Xuejiao Yang, Ming Du, Xin Li, Computer vision algorithms and hardware implementations: A survey,Integration, Volume 69,2019, Pages 309-320,ISSN 0167-9260, https://doi.org/10.1016/j.vlsi.2019.07.005.
[14] Bauer, C., Thamm, A. (2021). Six Areas of Healthcare Where AI Is Effectively Saving Lives Today. In: Glauner, P., Plugmann, P., Lerzynski, G. (eds) Digitalization in Healthcare. Future of Business and Finance. Springer, Cham. https://doi.org/10.1007/978-3-030-65896-0_22
[15] Roberts, M., Driggs, D., Thorpe, M. et al. Common pitfalls and recommendations for using machine learning to detect and prognosticate for COVID-19 using chest radiographs and CT scans. Nat Mach Intell 3, 199–217 (2021). https://doi.org/10.1038/s42256-021-00307-0
[16] The potential for artificial intelligence in healthcare, Thomas Davenport, Ravi Kalakota, Future Healthc J Jun 2019, 6 (2) 94-98; DOI: 10.7861/futurehosp.6-2-94
[17] Kelly, C.J., Karthikesalingam, A., Suleyman, M. et al. Key challenges for delivering clinical impact with artificial intelligence. BMC Med 17, 195 (2019). https://doi.org/10.1186/s12916-019-1426-2
[18] Ghassemi M, Naumann T, Schulam P, Beam AL, Chen IY, Ranganath R. A Review of Challenges and Opportunities in Machine Learning for Health. AMIA Jt Summits Transl Sci Proc. 2020 May 30;2020:191-200. PMID: 32477638; PMCID: PMC7233077.
[19] Sendak M, Gao M, Nichols M, Lin A, Balu S. Machine Learning in Health Care: A Critical Appraisal of Challenges and Opportunities. EGEMS (Wash DC). 2019 Jan 24;7(1):1. doi: 10.5334/egems.287. PMID: 30705919; PMCID: PMC6354017.
[20] Beyond Automation – Harvard Business Review. June 2015. Available from: https://hbr.org/2015/06/beyond-automation
[21] X. Bu, L. Lu, Z. Zhang, Q. Zhang and Y. Zhu, "A General Outpatient Triage System Based on Dynamic Uncertain Causality Graph," in IEEE Access, vol. 8, pp. 93249-93263, 2020, doi: 10.1109/ACCESS.2020.2995087.
[22] S. Safdar, S. A. Khan and A. Shaukat, "A Novel Data-Driven Adaptive Technique to Generate a Physician Visiting Schedule for Better Patient Experience," in IEEE Access, vol. 10, pp. 3935-3948, 2022, doi: 10.1109/ACCESS.2021.3138460.
[23] S. Safdar, S. Ahmed Khan, A. Shaukat and M. U. Akram, "Genetic Algorithm Based Automatic Out-Patient Experience Management System (GAPEM) Using RFIDs and Sensors," in IEEE Access, vol. 9, pp. 8961-8976, 2021, doi: 10.1109/ACCESS.2020.3046839.
[24] M. Cho, M. Song, S. Yoo and H. A. Reijers, "An Evidence-Based Decision Support Framework for Clinician Medical Scheduling," in IEEE Access, vol. 7, pp. 15239-15249, 2019, doi: 10.1109/ACCESS.2019.2894116.
[25] Li, X., Tian, D., Li, W. et al. Artificial intelligence-assisted reduction in patients' waiting time for outpatient process: a retrospective cohort study. BMC Health Serv Res 21, 237 (2021). https://doi.org/10.1186/s12913-021-06248-z
[26] Simini, F., Galnares, M., Silvera, G., Álvarez-Rocha, P., Low, R., Ormaechea, G. (2020). Pattern Recognition to Automate Chronic Patients Follow-Up and to Assist Outpatient Diagnostics. In: Ortiz-Posadas, M. (eds) Pattern Recognition Techniques Applied to Biomedical Problems. STEAM-H: Science, Technology, Engineering, Agriculture, Mathematics & Health. Springer, Cham. https://doi.org/10.1007/978-3-030-38021-2_8
[27] E. Bruballa, A. Wong, D. Rexachs and E. Luque, "An Intelligent Scheduling of Non-Critical Patients Admission for Emergency Department," in IEEE Access, vol. 8, pp. 9209-9220, 2020, doi: 10.1109/ACCESS.2019.2963049.
[28] El-Bouri R, Eyre DW, Watkinson P, Zhu T, Clifton DA. Hospital Admission Location Prediction via Deep Interpretable Networks for the Year-Round Improvement of Emergency Patient Care. IEEE J Biomed Health Inform. 2021 Jan;25(1):289-300. doi: 10.1109/JBHI.2020.2990309. Epub 2021 Jan 5. PMID: 32750898.
[29] A. R. Sharafat and M. Bayati, "PatientFlowNet: A Deep Learning Approach to Patient Flow Prediction in Emergency Departments," in IEEE Access, vol. 9, pp. 45552-45561, 2021, doi: 10.1109/ACCESS.2021.3066164.
[30] R. Jin, T. Xia, X. Liu, T. Murata and K. -S. Kim, "Predicting Emergency Medical Service Demand With Bipartite Graph Convolutional Networks," in IEEE Access, vol. 9, pp. 9903-9915, 2021, doi: 10.1109/ACCESS.2021.3050607.
[31] W. G. Allihaibi, M. Masoud, M. Elhenawy, S. Q. Liu, J. Burke and A. Karim, "Solving the Emergency Care Patient Pathway by a New Integrated Simulation-Optimisation Approach," in IEEE Access, vol. 9, pp. 100895-100910, 2021, doi: 10.1109/ACCESS.2021.3096263.
[32] B. Graham, R. Bond, M. Quinn and M. Mulvenna, "Using Data Mining to Predict Hospital Admissions From the Emergency Department," in IEEE Access, vol. 6, pp. 10458-10469, 2018, doi: 10.1109/ACCESS.2018.2808843.
[33] E. Kim, K. S. Han, T. Cheong, S. W. Lee, J. Eun and S. J. Kim, "Analysis on Benefits and Costs of Machine Learning-Based Early Hospitalization Prediction," in IEEE Access, vol. 10, pp. 32479-32493, 2022, doi: 10.1109/ACCESS.2022.3160742.
[34] Y. Wang, G. Zhang, L. Zhang, J. Tang and H. Mu, "A Column-Generation Based Approach for Integrating Surgeon and Surgery Scheduling," in IEEE Access, vol. 6, pp. 41578-41589, 2018, doi: 10.1109/ACCESS.2018.2854839.
[35] Y. Y. Luo and B. Wang, "A New Method of Block Allocation Used in Two-Stage Operating Rooms Scheduling," in IEEE Access, vol. 7, pp. 102820-102831, 2019, doi: 10.1109/ACCESS.2019.2926780.
[36] Nawaz Ripon, K.S., Henrik Nyman, J. (2020). Hospital Surgery Scheduling Under Uncertainty Using Multiobjective Evolutionary Algorithms. In: , et al. Big Data Analytics in Healthcare. Studies in Big Data, vol 66. Springer, Cham. https://doi.org/10.1007/978-3-030-31672-3_7
[37] Saleh, B.B., Saleh, G.B., Barakat, O. (2021). Operating Theater Management System: Block-Scheduling. In: Masmoudi, M., Jarboui, B., Siarry, P. (eds) Artificial Intelligence and Data Mining in Healthcare. Springer, Cham. https://doi.org/10.1007/978-3-030-45240-7_5
[38] A. Liu et al., "A GRA-Based Method for Evaluating Medical Service Quality," in IEEE Access, vol. 7, pp. 34252-34264, 2019, doi: 10.1109/ACCESS.2019.2903684.
[39] Mora-García, T.R., Piña-Quintero, F., Ortiz-Posadas, M.R. (2020). Pattern Recognition for Supporting the Replacement of Medical Equipment at Mexican Institute of Pediatrics. In: Ortiz-Posadas, M. (eds) Pattern Recognition Techniques Applied to Biomedical Problems. STEAM-H: Science, Technology, Engineering, Agriculture, Mathematics & Health. Springer, Cham. https://doi.org/10.1007/978-3-030-38021-2_9
[40] C. -C. Lu, S. -W. Lin, H. -J. Chen and K. -C. Ying, "Optimal Allocation of Cashiers and Pharmacists in Large Hospitals: A Point-Wise Fluid-Based Dynamic Queueing Network Approach," in IEEE Access, vol. 6, pp. 2859-2870, 2018, doi: 10.1109/ACCESS.2017.2785622.
[41] Z. M. Ibrahim et al., "A Knowledge Distillation Ensemble Framework for Predicting Short- and Long-Term Hospitalization Outcomes From Electronic Health Records Data," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 1, pp. 423-435, Jan. 2022, doi: 10.1109/JBHI.2021.3089287.
[42] T. I. Alshwaheen, Y. W. Hau, N. Ass'Ad and M. M. Abualsamen, "A Novel and Reliable Framework of Patient Deterioration Prediction in Intensive Care Unit Based on Long Short-Term Memory-Recurrent Neural Network," in IEEE Access, vol. 9, pp. 3894-3918, 2021, doi: 10.1109/ACCESS.2020.3047186.
[43] C. -L. Wu et al., "AEP-DLA: Adverse Event Prediction in Hospitalized Adult Patients Using Deep Learning Algorithms," in IEEE Access, vol. 9, pp. 55673-55689, 2021, doi: 10.1109/ACCESS.2021.3070618.
[44] Ippoliti, R., Falavigna, G., Zanelli, C. et al. Neural networks and hospital length of stay: an application to support healthcare management with national benchmarks and thresholds. Cost Eff Resour Alloc 19, 67 (2021). https://doi.org/10.1186/s12962-021-00322-3
[45] Cuadrado, D., Riaño, D. (2021). ICU Days-to-Discharge Analysis with Machine Learning Technology. In: Tucker, A., Henriques Abreu, P., Cardoso, J., Pereira Rodrigues, P., Riaño, D. (eds) Artificial Intelligence in Medicine. AIME 2021. Lecture Notes in Computer Science(), vol 12721. Springer, Cham. https://doi.org/10.1007/978-3-030-77211-6_11
[46] Munavalli, J.R., Boersma, H.J., Rao, S.V., van Merode, G.G. (2021). Real-Time Capacity Management and Patient Flow Optimization in Hospitals Using AI Methods. In: Masmoudi, M., Jarboui, B., Siarry, P.

(eds) Artificial Intelligence and Data Mining in Healthcare. Springer, Cham. https://doi.org/10.1007/978-3-030-45240-7_3

[47] Mellouli, T., Stoeck, T. (2021). AI/OR Synergies of Process Mining with Optimal Planning of Patient Pathways for Effective Hospital-Wide Decision Support. In: Masmoudi, M., Jarboui, B., Siarry, P. (eds) Artificial Intelligence and Data Mining in Healthcare. Springer, Cham. https://doi.org/10.1007/978-3-030-45240-7_2

[48] S. Jiang et al., "Combining Deep Neural Networks and Classical Time Series Regression Models for Forecasting Patient Flows in Hong Kong," in IEEE Access, vol. 7, pp. 118965-118974, 2019, doi: 10.1109/ACCESS.2019.2936550.

[49] H. Huang et al., "Discovering Medication Patterns for High-Complexity Drug-Using Diseases Through Electronic Medical Records," in IEEE Access, vol. 7, pp. 125280-125299, 2019, doi: 10.1109/ACCESS.2019.2937892.

[50] X. Zeng, S. Lin and C. Liu, "Multi-View Deep Learning Framework for Predicting Patient Expenditure in Healthcare," in IEEE Open Journal of the Computer Society, vol. 2, pp. 62-71, 2021, doi: 10.1109/OJCS.2021.3052518.

[51] Hutschek, U., Abele, T., Plugmann, P., Glauner, P. (2021). Efficiently Delivering Healthcare by Repurposing Solution Principles from Industrial Condition Monitoring: A Meta-Analysis. In: Glauner, P., Plugmann, P., Lerzynski, G. (eds) Digitalization in Healthcare. Future of Business and Finance. Springer, Cham. https://doi.org/10.1007/978-3-030-65896-0_15