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AI in Healthcare Operations: Optimizing Hospital Resource Allocation via Cloud Platforms

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Abstract: In recent decades, modern healthcare systems need to respond to the challenges of constantly increasing patient demand, a growing number of complex diseases, and patients with multimorbidity. This results in constrained hospital resources and limited financing from governments to effectively deliver care to patients. For operational decision-making, the timely forecasting of patient arrivals and resource demand is of utmost importance. Although the importance of forecasting has been recognized, analysing, monitoring, and forecasting multivariate time series in healthcare delivery systems remain challenging. Experts must become involved in system key performance measurement, resulting in significant resources being allocated to analyse and monitor processes but ultimately missing the timely nature of forecasting. This work develops a new hierarchical recurrent neural network (RNN) model to provide forecasts for a comprehensive resource allocation problem. First, a monitoring framework is developed to provide insightful analyses of operational difficulties. Also, a new deep learning framework is designed to leverage the derived univariate time series distributions and capture correlations at multiple aggregation levels using a hierarchical RNN framework to produce simultaneous forecasts of the timing and magnitudes of resource distribution.

In healthcare operations, resource allocation significantly influences healthcare delivery efficiency and patient wait-time, for which cloud computing platforms have been adopted and developed in hospitals. This review first identifies cloud-based AI techniques to aid healthcare operations literature and then uses a systematic dual-faceted framework to systematically review cloud-based AI applications in healthcare operations literature from three perspectives: type of AI techniques and methods, applications of AI in healthcare operations, and dimensions used to separate healthcare operations research problems. The findings reveal that (i) the cloud platform has been mainly adopted in healthcare as a cost-effective and efficient data storage and sharing solution, (ii) few studies have investigated the cloud platform’s value in AI-based decision-making optimization, (iii) cloud-based AI techniques are ignition-infrastructure to drive healthcare transformation, which justifies the need of more studies that develop and deploy cloud-based AI techniques to address healthcare operations optimization problems.

Keywords: AI in healthcare operations, Hospital resource optimization, Cloud-based hospital management, Predictive analytics in healthcare, Healthcare cloud computing, AI hospital resource planning, Smart hospital infrastructure, Machine learning in operations management, Cloud-enabled healthcare analytics, Real-time hospital data management, AI-powered patient flow optimization, Dynamic bed allocation system, Intelligent staff scheduling, Healthcare logistics AI, Operational efficiency in hospitals.

I. INTRODUCTION

Artificial Intelligence (AI) has become the foundation for many transformational challenges within the healthcare industry, especially given the increasing complexities when dealing with changing operational situations. Hospitals and healthcare systems are under pressure due to disastrous pandemic events, projected increasing demands of the aging population, and existing equity disparities among the underserved population. Technology advancement via digital transformations can tackle the existing challenges more efficiently. Emerging AI technologies such as machine learning and reinforcement learning can be the foundation for healthcare systems and other industries to build intelligent, operationally efficient, and socially beneficial systems of technology and processes.Recent advances in technology and available computing resources have brought about the emergence of cloud computing service platforms and deployment of hybrid cloud AI platforms. To expand the previously designed technology via cloud computing, there is a need to combat with the potential uncertainty and variability of parameters in vehicle routing problems (VRP). Healthcare in general and hospitals in particular need to look for a seamless way to allow healthcare databases to take advantage of cloud technologies together with the required security policies already satisfied. Unlike several well-researched topics outside healthcare such as autonomous vehicles for optimal ride sharing and dynamic path finding, healthcare needs to take these into consideration of the competitive and cooperative nature of healthcare systems.

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With recent advancements in AI, reinforcement learning (RL) techniques have been increasingly employed to manage demand forecasting, patient admission, labor shifts, inpatient flows, and bed utilization. Despite the relevant rapid advances and applications, the supporting RL platforms from the academic or commercial side remain unclear. The planned identifier and inputs depend heavily on the modeling techniques, and the RL or optimization algorithms under the dashboard are not as clear as they should be. To benefit administrators and the rest of the workforce, it is critical to scrutinize the purpose, advantages or disadvantages, modeling techniques, identifiers and inputs, and recent applications of using RL within the healthcare industry.

1.1. Background and significance

Decision makers in healthcare are faced with the challenges of optimizing healthcare operations. Healthcare operations are widely varied and include everything from patient scheduling to bed assignment. Enormous data resources and computational capacity in the healthcare sector are expected to garner value by deploying AI and analytics capabilities to liberate and exploit that value. However, healthcare analytics focusing on resource allocation in the operational domain is scant. Therefore, the practical importance of tackling this problem is huge but exposes grave academic challenges. One of the challenges is a large number of decisions to make. The number of decisions needed for CT assignment becomes prohibitive once there are many CT scanners. Another challenge is constant changes in the problem. Due to system changes (either planned or unforeseen), such as newly installed CT scanners, changing hospital staff, and demand changes, both CT usage distributions and resources are subject to changes.

Fig 1: AI in Healthcare Operations.

The same problems afflict many other problems faced by hospital administrators such as bed allocation, schedule-based surgical suite allocation, pharmacy inventory allocation, etc. Hospitals are also facing enormous data and AI opportunities. For these resource allocation problems, hospitals have gigantic databases of past usage data that describe the usage volume and profiles of the different resources–demand. Therefore, this research aims to develop a simple cloud delivered solution to optimal resource allocations given the demand profile, where input is demand profile(s) that can be obtained from historical data and output is recommended allocations based on usage distribution metrics under an analysis of tradeoffs. Due to computing restrictions, the hospitals may use a small-window control and only reallocate for new arrivals given the allocations for the others. Therefore, a QoS guarantee based model predictive control scheme is also proposed. Deep learning models are built to characterize learning components, the inputs of the resource allocation algorithms in the architecture, and the decision trees obtain near-optimal allocations to reduce the burden faced by the cloud platform.

II. UNDERSTANDING AI IN HEALTHCARE

AI systems encompass a wide range of computer-based technologies and tools that are capable of simulating human perception, cognition, and interaction with a focus on autonomous decision-making . For such systems to function independently, they must rely on a combination of hardware and software input, which is defined by a series of rules,

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laws, and models that dictate permissible responses to varying parameters. In the healthcare industry, medical AI can range from simple algorithms and mathematical computations used for analysis to increasingly complicated pattern recognition for measurement, diagnosis, and therapy. Implementing such technologies often requires modifying workstream paths, processes, and various subsystems on which the AI relies. Medical AI often requires additional datasets that must be created or acquired, another subsystem that is inextricably linked to success. Some training approaches, especially those modeled after deep learning processes, could require copious amounts of data that might need fabrication. Such new challenges turn on their margins, which can only be accomplished with more private stakeholder involvement, more detailed technological questioning by policymakers, and a higher threshold to launching novel technologies in highly complex systems.

Cloud computing refers to software, services, platforms, and application storage that are hosted on servers and devices that link over a secure internet connection. This processing can occur almost entirely off-device, thus eliminating expensive sensors and integrated chipsets. With this model, input from end-user devices is sent to cloud platforms over secure internet connections. The data is then interpreted centrally, returning fast results to the user. This extraction method has vast implications for AI. Deploying advanced AI systems call for large-scale distributed computing resources for storage, training, maintenance, and security, usually far exceeding organizational capabilities. AI relies heavily on data; therefore, it must have huge quantities of high-quality data to successfully train systems. Monitoring the quality of datasets is often out of reach for organizations; thus, resulting in degrading performance or harmful biasing and faulty results. Implementing such an information architecture while ensuring security and regulatory compliance is a staggering challenge for many organizations. Cloud systems can be expensive to maintain, thus increasing the risk of vendor lock-in; if the institution wants to switch providers further down the line, there are significant monetary costs incurred as well as logistical difficulties.

2.1. Definition of AI

Artificial Intelligence (AI) can be defined as the entire set of methods and procedures that involve the ability of a computer to imitate natural intelligence and the ability whereby itself is aware of its own existence, about the environment and can process the sensations of these aspects by applying reasonings and solving problems. AI can be divided into weak AI and strong AI. The former concerns AI systems in which an algorithm collects a number of parameters or variables corresponding to real-life features in order to build a model to reproduce the behavior of the observed system. This knowledge can be expressed with different types of formalism, such as mathematical equations or rules in the form of an expert system. The latter refers to hypothetical AI systems where the machine itself is cognizant of its own existence in the environment, which can drastically change the current perception of AI and its applications.

The knowledge of AI can be written down in a number of ways, e.g. in the form of equations, a mathematical model, a matrix of numbers, rules, or words within a natural language. This is not trivial because it limits the interpretability of the results, therefore hindering discussion and confrontation between the AI system and the human operatives. A great effort among the academic community is expected in the next future to develop ways to express clear knowledge out of the pre-existing knowledge-based AI. In the last few years, AI-based methodologies for medical diagnosis and medical decision support have gained much attention from the healthcare community and the public as automated systems for diagnosis and triage. The systems hold the promise to considerably optimize and accelerate the referral process to specialist appointments in case of urgent or critical findings. Within these contexts, AI has been proven particularly helpful in “information-rich” areas, where there is a considerable availability of in-depth and structured data to mine. Examples include the detection of cancers by means of molecular, genomic, and radiological data, the individual prognosis in the psychiatry field by means of cognitive and neuroimaging knowledge, the selection and identification of stroke patients by CT scans, the estimation of the risk of sudden cardiac death by means of ECG, the automatic classification of skin lesions by means of dermoscopic images, the finding of clues for diabetic retinopathy by fundus oculi images, the automatic detection of phenotypes correlating with rare genetic diseases from the photos of patients’ faces.

Equ 1: Objective Function for Resource Allocation Optimization.

$$\min_{\mathbf{x}} \sum_{i=1}^{N} (c_i \cdot x_i + w_i \cdot t_i)$$

- x_i: Binary decision variable (e.g., assign resource i)
- c_i: Cost of using resource i
- t_i: Time or delay associated with i
- w_i: Weight for penalty/delay
- N: Number of resources or tasks

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2.2. Historical Context

Available resources are distributed for healthcare services in a systematic manner. Resources can be defined as suitable for either a specific type of service or across different ones. An appropriate resource allocation using accurate methods is crucial, as any misallocation is likely to affect the outcomes negatively. In addition to potential shortcomings, healthcare operations consist of avenues for improvement, thereby producing the notion of resource saving. Resource allocation and resource saving can lead to two different types of practices, using a given resource in a better way (allocation) or exploiting a better way to improve resource production (saving). Healthcare resource management can be seen as a broader family, enveloping healthcare resource allocation and healthcare resource saving. In addition to a thorough definition, studies in healthcare resource management through additional abbreviations can be categorized in five ways by focusing on healthcare resource allocation and healthcare resource saving, healthcare resource management, or neither.

Matters on resource allocation in healthcare service emerged as early as budgeting processes. Resource allocation refers to processes determining the distribution of available resources across competing health issues. Since healthcare is a relative scarce resource, there is avoidable geographic bias in terms of resource allocation. Resource allocation is evolved as accountability for use of funds having been spent and used in provisioning, establishing a monitoring the decision making authority, using information systems as dominant tools. Besides, health service planning is end-oriented as decisions are only made in government and local authority levels. On the contrary, resource allocation as a research area emerges during the modeling and algorithmic framework to support the overall resource allocation decisions.

Distributed computing methods are being proposed and deployed on public shared systems or in private grids of inter-networked computers. Cloud computing is a new technology that aids hospitals in managing healthcare services and provides many application domains. It consists of a significant amount of on-demand computing resources, which send and/or receive data over the Internet.

2.3. Current Trends

AI technologies are being rapidly applied to healthcare operations in various ways, including optimizing hospital resource and personnel allocation via cloud platforms. It is applied currently to address utilization of facilities by taking into account heterogeneous resource types and accidental treatment costs. These capacities were further utilized to develop algorithms for minimizing specified treatment costs for specified workplace accident rates. Specifically, hospital personnel scheduling is studied using cloud-based hyper-heuristics (HH) and CloudSim. Because of scheduling complexities, HHs have been proposed, evaluated, reused, and combined in cloud platforms. Because similar challenges are increasingly examined by medical resources scheduling, a focused platform for cloud-based HHs is developed, accompanied with a case study of treatment amount maximization for a cancer care hospital. Regarding scheduling personnel for the healthcare sector, hyper-heuristics (HH) have gained recognition for scheduling complexities and have been carried to the cloud. The platform is targeted at deploying and evaluating cloud-based HHs for such complex scheduling, along with user-friendly interfaces to improve accessibility, including a scheduling case study inspired by cancer care scheduling. The proposed algorithms can be served as standalone or web service. In this topic, cloud-based HHs for scheduling blood collection center staff are introduced. Addressing the special complex work-rule and uncertainty demands, multiple problem encodings and heuristic approaches are examined to enhance solution quality and robustness. Finally, utilizing cloud resources and parallel computing, they tackle a resource scheduling problem for patient treatment in a multicenter breast cancer information system. The focus procedure, hospital facilities, and personnel can all be scheduled to minimize treatment costs. Further extensive experiments on health insurances are also conducted to evaluate the application feasibility on cloud-based systems. It is to be applied to scheduling healthcare resources and personnel to explore the potentialities of the cloud technologies for healthcare service providers.

III. CLOUD COMPUTING IN HEALTHCARE

Data stored in cloud platforms can be accessed by hospitals through applications that use data analytics, increasing significantly the data usability and providing hospitals with better tools to manage and improve their operations as well as providing new services. Cloud computing is highly scalable and as demand increases the capacity can easily be upgraded avoiding higher costs associated with on premises hardware. Due to its nature cloud computing provides high availability and redundancy of data storage, making it more reliable than typical on premises storage. These features can help hospitals servers take advantage of these technologies to improve patient safety and care using the available decision support tools in the cloud.

On the consumer’s side cloud computing is also becoming more popular. The increasing number of smartphones and the possibility of being connected to the internet from almost anywhere have changed the way things are done. Instead of

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going to an office to get work done, many tasks can be done online, and new services are becoming available for health and wellness management. Patients can be informed and managed using tools available online or using apps for smartphones, tablets and personal computers. In this case, hospitals can complement traditional patient treatment and follow up with web-based services.

3.1. Overview of Cloud Technologies

In this section, the concepts of cloud computing and its various services will be reviewed to understand the significance of these technologies in healthcare operations to optimize clinic resource allocation. Cloud computing is an on-demand self-service network-enabled computing resource provision in terms of a pool of configurable computing resources that can be quickly provisioned. Resources can be in the data center, such as networks, servers, storage, applications, and services, needed to process and analyze data. It offers scalable and seamless services that can be accessed over the internet from different devices. Cloud computing has generated a paradigm shift in computing technology and service model for many domains. It can be rented and used with a pay-for-what-you-use model, unlike grid computing. Considering the attribute of cloud computing, it is more scalable, elastic, and noble than grid computing.

Cloud computing has provided an opportunity for both growth and cost-cutting in various global businesses, including health care. It has become an ideal information technology for health care as it allows immediate and remote utilization of computing resources and applications. Cloud services can provide platforms to collect, store, process, analyze, and share health care data on costs and the scale of information used. These services can also provide collaboration platforms among clinics, hospitals, health care professionals, and patients. As a result of recent developments of wireless Internet technologies such as 3G/4G, Wi-Fi hotspots, tablets, and smartphones, interest in the use of cloud in mobile health governed by health care organizations and companies has recently increased.

3.2. Benefits of Cloud Computing

In recent years, cloud computing has been a major focus of commercial and academic research. In particular, due to its cost-effectiveness, flexibility, and global reach, cloud computing has emerged as one of the most vital technologies for healthcare service providers. Cloud computing refers to the utilization of reusable IT resources that can be dynamically allocated and released based on consumer demand. Such services can be accessed when needed and paid for on a per-use basis.

In the healthcare domain, high-quality services can be provided through cloud computing infrastructure, and reliance on the cloud can free healthcare service providers from infrastructure concerns. For example, essential medical hardware such as imaging systems can be large and expensive, making it impractical for an individual provider to manage such systems on site, even if they are needed only rarely.

Instead, cloud-enabled delivery of imaging equipment, including radiology, ultrasound, and laboratory equipment, is rising. By compressing the medical images, anxious patients can commence their diagnosis before they reach their doctor's office.An effective software-based E-Health application should include monitoring data collection and storage, eventual data analysis, response generation, and result presentation. Compared with in-house treatment, cloud computing brings significant benefits, such as pay-as-you-go pricing models, improved utilization of IT resources, high-quality service delivery, and reduced maintenance and security concerns. E-Health systems can also gain from cloud computing through the potential for shortening access time for health providers to data repositories.

The cloud system is independent of physical location, unlike conventional files stored on a hard disk. Multiple agreed users can access the same files even from different devices, and a user can still access the files even if the device the files are stored on is damaged. Later investments in IT infrastructure can take advantage of advancements in computing technologies without necessitating the replacement of outmoded systems. The architecture and mechanisms of e-Health systems in the Azure cloud and benefits from using the cloud are discussed in the following sections.

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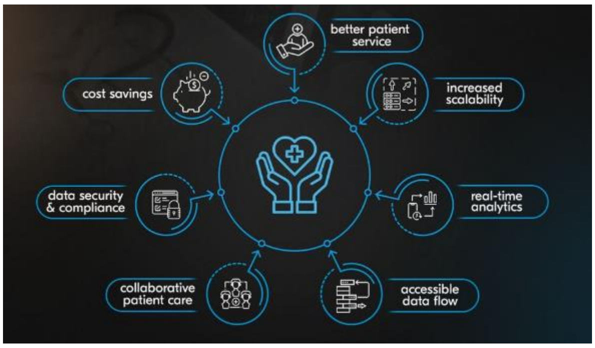

Fig 2: Benefits of Cloud Computing in Healthcare.

3.3. Challenges and Limitations

Public attitudes towards AI technologies can fluctuate, depending heavily on attitudes towards technology in general and previous experience with government programs. Issues such as the ethical use of AI in determining eligibility for healthcare services, training data, and racial bias in prediction may deter support.

On the level of the health system, some countries lack the capacity for a national AI strategy. Where a strategy is formulated, the lack of political and financial support, as well as insufficient stakeholder engagement, may hinder its implementation. In some countries, the wide-spread introduction of AI programs is hindered by the absence of appropriate regulations and legislation. Recent efforts to regulate AI across the European Union may further complicate the introduction of healthcare AI programs.

The introduction of AI in the healthcare system may also be limited by the capacity of the public to adopt new technologies. A lack of knowledge regarding AI, as well as anxiety regarding the safe implementation of AI systems in healthcare, may lead to resistance among stakeholders who are not well-prepared to cope with the rapid introduction of new technologies. Despite a lack of knowledge, the introduction of AI may also trigger skepticism regarding the healthcare sector collecting and analyzing data in a new fashion.

IV. RESOURCE ALLOCATION IN HOSPITALS

In order to use the hospital's intensive care units as efficiently as possible, compromise must be found between getting the most out of them in the best way, and the care of the patients. Building a deterministic model. Those are the aims of the model; to optimize which patient should move to which intensive care unit, so that total travel time is minimized, thus defining the quality assessment. The potential optimization strategies considered are based on the idea of allocating patients in order of severity. The models will be very basic; initial models will not take time windows into account and will explore a variety of other factors in a successive series of iterations. Stochastic models and considering more factors will make the model and its solution more realistic. The optimization approaches are a challenge due to the mixed binary nature of the models, and a range of heuristic and metaheuristic algorithms will be implemented. The latter will be tailored in order to show how different parameters, including the potential optimization strategies, affect the quality assessment of planning decisions. It is necessary to examine the effects of the different parameters so that their relevant weights and ranges can be implemented in future applications of the optimization model.

A deterministic optimization model will be built with the aim of minimizing unnecessary travel times of patients in a hospital with multiple intensive care units. The key idea is to identify the most efficient transfer patterns whenever a transfer of a patient is initiated. A set covering formulation will be developed, and its computational feasibility will be investigated. Analysis of real life data shows that a simple pattern identification method can solve constellations of moderate size quickly with an optimality guarantee. I.e., this procedure is a promising approach to enhance transfer rate while keeping travel times low in a cost-efficient way. It is supposed to be of general interest as it may be applicable to other transfer scenarios and an important topic for further research.

4.1. Importance of Resource Allocation

Healthcare is a generalized concept that can be categorized into different healthcare systems according to its management approach. From an operational management viewpoint, different institutions play distinct roles in effectively managing the healthcare delivery processes and patient flow. Each healthcare institution manages its own resource allocation based on fixed budgets or patient capacities, including how many doctors to deploy in which departments and at which time.

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Hospital resource allocation generally has an enormous spatiotemporal search space. While search heuristics and constraints greatly ease up the searching burden, healthcare economics is still highly influenced by outlier scenarios. This imposes outrageous operational costs on hospitals from inefficient to improper resource allocation decisions. Recent studies in healthcare economics utilize artificial intelligence techniques to measure outcomes of resource allocation decisions for a single hospital. Yet, the analysis of a whole hospital network remains a challenging task. Recently, healthcare systems are seeing wide adoption of cloud platforms for enhanced resource allocation and ecosystem collaboration. Decentralized hospital cloud platforms reduce the overhead for diagnosis, treatment and recovery of patients, yet they significantly hinder the resource allocation across hospitals. Such types of systems are crucial either for large healthcare networks or resource-constrained regions.

Fig 3: Importance of Resource Allocation.

The goal of the research is to develop, implement and evaluate a cloud-based AI system for optimization of resource allocation of a hospital network. The core contribution of this research is a two-level deep learning framework and a resource allocation algorithm trained with heterogeneous resources managed by different hospitals, which communicates through a cloud platform. The primary benefit of the framework is that it generally approximates the highly complex but largely under-constrained resource allocation scenarios in the real world with heterogeneous attributes. The proposed algorithm for complex soft appointments improves the overall house utilization of a hospital network without under-utilizing a single hospital. Applications and evaluations of the system on a real-world case of a hospital network demonstrate that it is capable of generating actionable insights to improve overall healthcare economics with high precision. AI in healthcare economics fills in the gap of studies on multi-hospital resource allocation decisions. Additionally, cloud-based platforms enable scalability and inter-institutional contribution across hospital networks in any healthcare system.

4.2. Current Practices

In the past few years, numerous studies have been conducted to analyze hospital operations and patient flows. Focus points include patient arrivals, lengths of stay, and capacity utilization. Multiple factors influencing healthcare economics arise from nutritional, geographic, or demographic variables. Random forests outperforms supervised ANN, GLM, and boosting methods, and accounting for this method leads to a better understanding of variables that explain differences between hospitals.

Various systems have been used for sharing and distributing healthcare resources. Resource allocation is the allocation of available resources among competing uses. Current systems that generate forecasts for decision making tend to use ad hoc, expert-driven models. Resource sharing in public institutions is based on policies by the government and is mostly an opinion/expertise-based process. In a shared economy, organizations or people with infrequently-used resources contribute their assets into the marketplace, on which resources are allocated for a fee. Given the expertise-based, ad hoc decision making processes, large amounts of documents are required to be extracted to find cases of interest, and forecasts are usually inaccurate, spending enormous efforts in decision making. Methods for efficient sharing provide information on potentially available resources instead of one's own, and are inappropriate for fair resource allocation.

4.3. Impact on Patient Care

AI can help hospitals, government, and health agencies by analyzing daily records from hospitals and clinics to understand patient volume trends. An AI model compares current volumes to historical values to determine if they vary significantly, informing those in charge when to address an increase in patient volume. AI can also greatly improve resource management by ensuring that the right decision is made when reassigning staff and providing hospitals with a tool to strategically make adjustments when and how much needed staff or resources should be reassigned. With a calibrated model, an AI approach can detail how to use statistical analysis to match patients to beds within a specific unit by day, instead of having it done parametrically every week, saving about two weeks of administrator time. AI-based

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cloud platforms track volunteer actions and information about health conditions or epidemiological trends to help hospitals, government, and community organizations bill for volunteer hours and track whether enough volunteers are on hand. This can also advocate for telehealth and allow doctors to treat a larger population while still assessing patients at the same 10-minute intervals.

Healthcare system mass casualty events can be planned for by determining decision points long ahead of time and ensuring a playbook is in place to prevent issues with shifting contexts. Reallocation and replacement of operational health resources can be made easier following an event with a cloud platform that tracks workflows, where all coordination between agencies follows a defined mechanism. Overall health alliances for data analysis, investigations, and resource management can create a clearer picture of actions to take in exchange for the ability to track healthcare system status across an entire country. A standard policy network solely focused on social and economic welfare could be trained on action and outcome data from countries around the world to produce hospitable policies for dealing with mass casualty events.

V. AI APPLICATIONS IN RESOURCE ALLOCATION

Artificial Intelligence (AI) can augment and support operational decision making across various domains and industries, including healthcare. Yet a systematic inquiry into the current AI landscape and areas for future research in operational applications in healthcare is still lacking. To address this, a comprehensive analysis of the research literature on AI in healthcare operations is conducted, with a focus on a novel big picture taxonomy of healthcare operations activities and its constituent task types. The underlying methodologies used in AI healthcare operations research are also examined. An online scoping review of 309 literature was conducted, and various knowledge gaps and future research directions were identified. Particularly, it was discovered that (1) most research applying AI in healthcare operations only focuses on modelling complex problems without solving them; (2) AI functionalities can be applied to both the input and output sides of healthcare operations' models for treating input-related and output-related problems respectively; and (3) a number of AI functional capabilities and healthcare operations task types have not yet been extensively examined, pointing to fruitful opportunities for future research.

A data-driven approach is presented for the modelling, simulation, and optimization of resource utilization in any healthcare institution regarding the COVID-19 pandemic. The objective of this research is to optimize the resource allocation strategies of hospitals based on the cloud platform with Artificial Intelligence (AI) for the concerned stakeholders in the system. The framework of this research gives a holistic view of the implemented platform and how the stakeholders can benefit from the analysis of various AI techniques and simulation models. The cloud platform is an end-to-end platform built on the existing data acquisition technologies in hospitals. Using the collected datasets, the resource allocation optimization model is proposed with four decisions to minimize the choosing cost and unexpected waiting time. Various simulations and AI analysis are also proposed to assist stakeholders in the healthcare systems with visualizations of the inputs. The results show how the healthcare systems can benefit from using the proposed framework and the corresponding analyses.

To satisfy the COVID-19 pandemic requirement, the data acquisition was planned during the COVID-19 pandemic, in which the system should have defined the daily needs of various resources optimally. The proposed deep learning architecture is used to model and analyze the data. Although it is challenging to collect moving hospitals datasets, the model can optimize mobile hospitals to be used for the current paradigms, such as block chain in an IoT environment. Building the cloud platform is a big milestone for the healthcare systems to further analyze usages on various hospital aspects to benefit project management in hospital implementations.

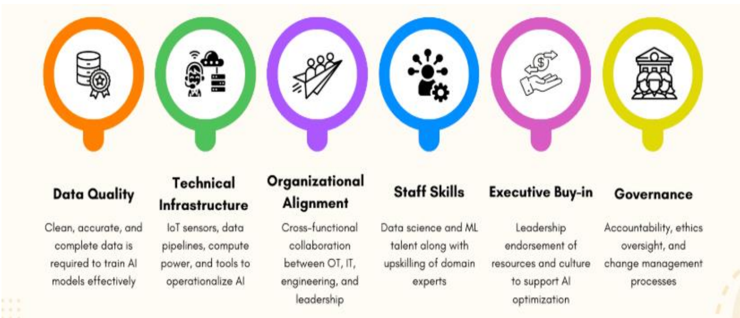

Fig 4: AI Applications in Resource Allocation.

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5.1. Predictive Analytics

Predictive analytics refers to a broad range of statistical techniques from predictive modeling, machine learning, and data mining to analyze current and historical facts to make predictions about future or otherwise unknown events. In healthcare, it is having a substantial impact on how hospitals operate. In many cases, it leads to a reduction in operations costs. In further cases, it will be a decisive factor for the future viability of hospitals. Effective resource planning and timely decisions can prevent a costly shortage of resources. Accumulated data can be mined for valuable information that helps to better understand the mechanisms influencing resource scarcity and occurrence. These insights can be used to generate relevant predictions regarding resource utilization in the future. Based on these forecasts, capacity adjustments can be triggered automatically or suggested to decision-makers.

A hospital is a complex system that consists of many sub-processes, such as inpatient and outpatient care, monitoring, and diagnostics. Daily scheduling decisions are often taken manually. Due to the complexity of the interactions associated with the various waiting lines, it is impossible for a human planner to consider all the direct and indirect effects when devising a schedule for the next days. Therefore, current planning systems usually act reactively. This means that either the scheduling is done on a day-to-day basis or a rolling scheduling task is performed for one or two weeks into the future. However, the further into the future the planning task is executed, the less control a hospital has on relevant parameters such as physician resources or the admission of new patients. Hence, not only utilization but also admission processes may start to destabilize. But how can a hospital quickly assess the effects of such a decision without having to follow the standard procedure of collecting and formatting data, running a simulation study and analyzing its results? Hospitals can utilize predictive approaches that derivatively, from existing simulation models, can help summarize future scenarios with a reduced time and computational effort. In hospitals, where historic data is abundantly available, it is possible to generate knowledge on the behavior of the underlying system by means of data-driven approaches.

5.2. Decision Support Systems

The decision support system in a hospital is critical for making decisions in patient care and treatment. Various factors and sources of information must be integrated in a structured manner. For example, many hospitals now have cloud platforms capable of processing massive data. The information is then processed by various machine learning algorithms for predictability. Healthcare has made great changes in adopting artificial intelligence-based clinical decision support systems.

Using this training manuscript as a guideline, there are four periods of decision support system in the hospital. The first period is after management thinking about decisions and then adopting various techniques and methodologies as decision support systems. The key mission is on modeling decisions with new techniques and methodologies. Traditional techniques are implementation focused. The second period is in need of modeling with difficulties. The incomplete data set is common because patient information is recorded. It is necessary to investigate measures of statistical properties like bias and outliers. A serious obstacle stands in how to scientifically model incomplete data. The third period is on decision uncertainties. It has challenges when there are important decisions in healthcare economics. The complex environment results in critical uncertainties of realization of decisions. The disasters either external or internal could greatly affect not only the medical but also economic aspects of hospitals. Weighted scoring and multi-attribute decision methods are pursued to suggest suitable treatments.

Four methodologies are proposed to evaluate the optimized medication policy of hospital units. A theory-based cutting-edge methodology is also innovated. Conventional decision evaluative methodologies focus on simulation and mean deviation of simulation outputs. They fall short in suggesting validated policies to managers. As outlier events occur, hospitals that are either external or internal could meet critical uncertainties for realization of policies. Existing cloud platforms are capable of processing massive data on patient flow, census distribution, etc. The data can be further processed by various machine learning for predictability.

5.3. Scheduling Optimization

The importance of scheduling operations in regard to delivering efficient service quality of Major Equipment for Pathological Examination systems was analyzed. Following the methodology in this work, managers may know the most optimal assignment of the pathologist's shifts, determining how the personnel rearranging can improve the service quality by more than 2%. It is important to remember that every operation in the proposed model may also take an individual decision, but the simultaneous analysis was the main focus of this work, reinforcing that the model can obtain insights on how different assignments may affect the KPI metrics.

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The ultimate goal would be to obtain a multi-unit scheduling priority approach when also taking into account the analysis of multiple workloads, not only the average service time. Dealing with the fluctuating load of a system where there are Expert Pathologists, it would also be interesting to apply different weights concerning the diagnostic cost of mistakes if it is known a priori, opening a door for future work. It is suggested a later and more fine-tuned work on the application of the proposed solution as a decision tool in the PMS considering the previously listed limitations, as well as applying the solution to similar Pathology labs with an exhaustive data collection and analysis to then consider the tool the first line in decreasing the service level volatility in those labs.

It is important also to deeper re-check the results regarding simulation statistical issues, concentrating more in there for the sake of leading to a simple Meta-Heuristic or Randomize Simulation Execution methodology. Cloud scheduling is an emerging aspect of scheduling. More and more companies are moving their operations to the cloud to improve performance and save cost. Scheduling of cloud tasks is critical since it can affect the quality of service and completion time of jobs. There are different techniques that have been proposed like genetic algorithms, behavioral-based cloud scheduling approaches etc. But none of the approaches use a benchmark comparison of the established techniques.

Hence there is scope for applying known heuristics such as ant colony optimization, particle swarm optimization etc in a hybrid manner to explore the trade-offs between job completion time and cost and implementing in the cloud context which is mostly unexplored.

Equ 2: Machine Learning-Based Demand Forecasting (Linear Regression).

$$\hat{y} = \beta_0 + \sum_{j=1}^{p} \beta_j x_j$$

- $\hat{y}$: Predicted demand (e.g., patient admissions, bed occupancy)
- x_j: Feature variables (time, weather, diagnosis codes, etc.)
- β_j: Model coefficients
- p: Number of features

VI. INTEGRATING AI WITH CLOUD PLATFORMS

Cloud computing and edge computing have gained great momentum in recent years. Cloud services deployed at cloud data centres can provide a broader coverage and a larger resource pool, which enable various resource-intensive applications such as video analytics using deep learning based approaches. Edge devices are designed to carry minimal computing power and provide local functionalities with limited computational workload. With the growing number of connected sensors and actuators at the edge, the cloud-edge computing architecture calls for stringent research opportunities. The emerging cloud-edge computing architecture can bring tremendous opportunities to accommodate more massive machine-type communication devices while supporting a broad class of applications with diverse requirements.

The heterogeneity of resources and communication technologies in cloud and edge networks, together with the differentiation of application demands, call for advanced resource and service management techniques. As an indispensable part of the cloud-edge computing architecture, resource and service management plays a central role in orchestrating cloud and edge resources to fulfil the requirements of edge applications. With the advancement of IoT and AI technologies, resource and service management is evolving from traditional techniques heavily depending on expert knowledge to an autonomous and intelligent paradigm. A deep learning based framework could be built to realise intelligent resource management in AI applications.

Emerging technologies, such as the Internet of Things, big data, blockchain and artificial intelligence, are transforming the way healthcare services are being delivered around the world. Although these technologies show immense potential to improve the quality of healthcare services, the operationalisation of such advanced technologies within health services have proven challenging. AI, in particular, has been attracting increasing interest as it provides opportunities to improve and augment healthcare professionals' capabilities through better and more insightful data driven solutions. However, AI technologies are still in their infancy regarding widespread implementation into integrated solutions that could enhance service delivery in the healthcare system. A state-of-the-art review was conducted to investigate current applications, challenges, and practices surrounding AI in healthcare. Different definitions describing hospital processes are suggested and diverse aspects that may complicate the adoption of AI within health services have been recognised.

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6.1. Frameworks for Integration

The work on the interconnected healthcare ecosystem offers a wide-ranging framework for integrating healthcare operations through cloud-based platforms. Within this framework, both cloud and edge platforms are envisioned to play key roles in the storage and analysis of data generated by IoMT devices. This work has investigated the challenges involved in the management of healthcare operations settings that are connected in the cloud or edge, with a specific focus on cloud or edge platforms. In healthcare operations subject domains, three use cases have been used to motivate the research directions and possible applications. In addition to the findings and frameworks, this work has identified future research opportunities to further enhance the understanding of the interconnected healthcare ecosystem towards developments of practical solutions. The Healthcare Hub centered on the cloud platform offers integrated operations by connecting a number of healthcare settings. Such a hub can consider the service requests from all healthcare settings in its area and route the requests to the best-suited healthcare settings considering the patients and practitioners, enabling optimized allocation for patients trying to book appointments across healthcare settings. Moreover, optimization approaches operating under various uncertainty structures have been explored to support patients, setting quality managers, and healthcare systems in analyzing the uncertainties and effectively managing possible risks in a holistic way. Resource allocation within healthcare settings investigates the assignment of requests and/or resources to the scheduling slots. Two intelligent resource allocation frameworks have been proposed and investigated for mass vaccination setting and value-assurance scheduling in medical imaging settings, respectively. The intelligent system architecture learns and realizes data-driven automated management of healthcare settings while ensuring compliance with decision-making requirements. The generalizability and practicality of these two frameworks have been demonstrated through modeling and evaluation of various types of appointment requests and resources in a wide range of healthcare operations.

6.2. Data Management Strategies

Healthcare operations involve numerous interrelated domains, such as patient management, infrastructure management, doctor management, equipment management, alert management, and storage optimization. Each of these domains generates large amounts of data over numerous chronic diseases, which are valuable for assessing the performance of healthcare operations and making decisions. Due to the involvement of various interrelated domains, domain consistency has to be maintained. Failure to do so causes the day-to-day operations to be inefficient. Typically, multiple heterogeneous subsystem applications are used for modeling each domain care operation in hospitals. Some serialization/standardization operations are needed for data transfer among subsystems. However, scaling to multiple hospitals has limitations in terms of performance and data protection due to more data accumulation. Therefore, a cloud platform needs to be developed for addressing the issues of in-connected data management. Cloud-DP has to be developed for a distributed architecture for connected healthcare operations in hospitals. Feasibility of sharing in the cloud platform among multiple hospitals is analyzed and an edge computing-based design solution, cloud-edge DP is proposed. On the edge, the distributed data is accessed over flexible abstraction for design purposes. On the cloud, a Markov decision process-based data management shows the confidentiality of distributed operations. The cloud-edge DP is demonstrated over synthetic datasets and with a case study for the acuteness management.

Due to the move from Electronic Data Archives (EDA) to Internet of Things (IoT) eHealth, new healthcare infrastructures generate cloud-based big data of a dynamic scale. Since the volume of data obtained through constant monitoring rises steadily and is complemented with user-generated unstructured data, big data strategies and analytics must be given attention. The significance is discussed by expanding on how the spectrum of big data is relevant to eHealth and medical operations, particularly in terms of clinically relevant information derived from rare event macro and continuous data. Yet, the rapidity of data collection compared to data analysis is an issue. These approaches expand on and encompass a rapid data collection paradigm and accelerate computation and re-calibration methodologies for analytics, as well as the distribution of buried structures in monitoring data. Therein, a discussion of the constraints imposed on sampling paradigms, and its relevance to mathematics principles and relevant sampling theorems in the field is focused on. Specifically, it involves diagnostics and interventional imaging at the limits of regularity in data handling.

6.3. Security and Compliance Issues

Healthcare organizations have to fulfill various legal and compliance requirements. An enforcement of the HIPAA compliance regulations is crucial for health insurers and healthcare providers that process health information. Under the HIPAA, appropriate safeguards should be in place for the protection of personal health information and measures taken to improve security awareness. Apart from the legal risks with non-compliance, there are also individual privacy risks due to unauthorized access to health databases. With the rapid growth in the number of Cloud EHR systems and patients storing their health data on cloud databases, the risk of such data being compromised is felt to be increasing. A growing number of breaches in personal privacy and health data security have been witnessed. It is thus necessary to identify potential risks, breaches, and vulnerabilities in existing Cloud EHR systems to make them more secure.

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The e-health Cloud service intelligence model for effective access control management has been developed that intelligently updates the security domains of knowledge about sensitive data. The Architecture and design of remote data auditing schemes for dynamic data are continued. The cloud provider not only provides storage services but also possesses the health data which is not a genuine assumption and hence abuse the second party audit idea in an untrusted environment is challenging. Security and privacy aspects have to be preserved so that health data remains incognito and a third party cannot learn about it. System keeps an outsourcing service, a verifier, and a cloud user and a cloud user is not able to send a request for verification unless he holds the requisite secondary credential for the data to be audited.

Attacks and vulnerabilities of the healthcare workflow process on cloud computing and fog computing architecture have been presented. Security issues and defenses vary in different cloud architectures. It has been explained why the traditional risk analysis methods cannot be reused to validate the security of emerging cloud architectures. A systematic approach has been provided to describe potential attacks on cloud architectures. How the workflow process can be affected by attacks has also been illustrated. With the risk evaluation tools and criteria set up, an automatic security evaluation tool has been designed to generate heuristic evaluation reports with requirements and countermeasures.

VII. CASE STUDIES

Research literature has advanced multiple methodologies to predict patient arrival traffic, addressing the linear regression issue in the past. And, while some methods seem to successfully outperform existing models, in practice it is rather common for institutions to keep the existing approaches based on these very long standing algorithms. Thus, one avenue of investigation is to study the set up of an easy to deploy benchmarking platform, deployed on a cloud infrastructure, to assure availability of resources. Since one of the hardest issues in the early deployment is somewhat stuck into bad and nasty topologies this cloud environment can make use of recent advances in representation theory for complex networks. To address the move towards a bigger number of intense analysis of data resources, health care centres can deploy analyse allocation resources in cloud infrastructure. This distributed approach will mostly resolve one big problem of localised infrastructures on compute size is the exact traffic anticipated. Thus, this benchmarking cloud environment will be able to assess through concurrent processing of data sources to find the most suitable infrastructure and methodology to balance computational resources for the second most important step for cloud allocation of resources: data collection and cleaning.

Many challenges exist for hospitals before quality improvements can be assured through wide-scale AI adoption. Many AI applications are designed to work within the context of a hospital where it can use existing data formats and datasets. There is a wide scope to benefit in terms of time savings, reduction in human error, and increased safety from a new picture recognition and AI-based system. Cloud healthcare platforms should address data format compatibility challenges with legacy hospital systems for smarter data collection. This is a focus of many of the use cases in this project. Such co-development and evaluation of AI applications should be contingent on the requirements of existing practices, since these are often more complicated than the intended matching use case. There is an unprecedented lack of sharing during the initial stages of deploying new technologies.

7.1. Successful Implementations

Electronic bed planners, RER, harness four schemes to develop cloud-based routine patient route scheduling and real-time dynamic rerouting systems. Both schemes offer favorable performance in the event of weekday OT appointments and patient arrivals at MBUs. In the event of pushback on bed allocation at MBUs, RER's hybrid scheme shows the most optimal performance. National health service coordinators in Denmark relied on a cloud computing-based approach to develop a decision-support system for predictive capacity management, assessment of hospital types and size, and resource allocation/reallocation to hospitals under the patient cohort. Utilizing cloud computing, GRS is being developed at Finland's largest hospital to renew inpatient admission flow and consists of a knowledge layer, a database layer, and an interface layer. The predictive demand model provides daily hospital-level forecasts by implementation period. Predictions are automatically submitted to the dispatch and resource allocation module in GRS cloud computing.

RER, a cloud computing-based AI technology, has been advanced to offer an interactive BOAT for pinpoints to executive in-patient bed service planners and managers when there are no assignments for tactical patient allocation schemes. Dynamic information is fed through Result Extraction to propose candidates, which aids decision-making in handling accelerated hard-to-cope predicted admissions/OT patients. The Health Data Collaboration Research Platform assists health system decision-makers, planners, and managers engaged in assessment and optimization of healthcare service delivery. To alleviate congestion, team managers may identify affected teams and likely causes via the Landing Analysis module. Collaborative exploration of need and provision for the post-pandemic phase is conducted in the BMHS and BTL systems. Prior to the COVID-19 outbreak, both systems contributed to substantial improvements in hospitals'

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COVID-19 responsiveness. In addition to the dynamic scheduling of in-patient beds, proactive scheduling of operation theatre (OT) resources and preparation services for out-patient appointments could benefit from deep learning.

7.2. Lessons Learned

The findings from this study provide valuable insights into the effectiveness of AI-enabled cloud healthcare systems in optimizing hospital resource allocation. One of the key learnings was that AI-based dashboards have the potential to serve as a decision-making and monitoring tool for hospital administrators, allowing them to assess whether their current resource availability is adequate or if they need to seek additional support or share their excess resources. In addition, the results of this research provided unbiased information about how resource sharing is present in certain scenarios through the use of additional sequential recommendation questions with factor specification so that the cloud platform can provide greater accuracy in its responses.

Additionally, a genetic algorithm-based binary route suggestion model can provide unbiased recommendations about whether a cloud platform should receive a request for support. Furthermore, the TSP with a genetic algorithm can output unbiased research-based route suggestions according to certain factors, such as cost and distance. There are, however, still limitations in terms of experimentalization and public data. A suggestion intended for future research is to iteratively improve AI and hybrid models so that they are able to automatically expand their usability and effectiveness, resulting in a win-win relationship for all parties involved in the healthcare network. A second recommendation is to optimize inside cloud platforms to maximize service value by transforming wasted construction efforts into shared values for greater transparency and resource availability.

It is hoped, in the long run, that this study can aid healthcare networks in achieving further optimization capabilities through the combination of AI and cloud platforms. With this optimized resource sharing, the sustainability and resilience of the entire healthcare ecosystem can improve. In an environment where national budgets and populations are growing increasingly stressed, the healthcare industry must prepare for greater waves of challenges than ever. Establishing an AI-enabled cloud healthcare network to optimize resource allocation can benefit the situation and, most importantly, enable better caregiving to those who are in need.

Equ 3: Queueing Model for Patient Flow (M/M/1).

$$L = \frac{\lambda}{\mu - \lambda}$$

- L: Average number of patients in the system
- λ: Arrival rate of patients
- μ: Service rate (e.g., treated per hour)

7.3. Comparative Analysis

Five recent works focused on optimizing the allocation of resources in smart hospitals were compared to the developed model, highlighting some of the similarities and differences concerning problems/solutions addressed, obtaining data and resources, and evaluation metrics. The comparison is summarized in TABLE 5. As can be seen, the model developed in this paper stands out for being aimed at a proactive use case, which is more suitable for smart hospital environments. Moreover, this model employs historical data as input information and considers different types of health resources. Finally, the use of constrained linear programming as a solution method allows the model to generate quick results, which is an advantage in dynamic scenarios. However, it should be noted that the other models developed advanced works in general. Five works were surveyed, and a comparative analysis with the model developed was performed. Each model was analyzed considering the aspects presented below.

Preventive or reactive approach: All five models were addressed from a preventive approach. Vati et al. proposed a preventive model to optimize the allocation of beds in several types of wards. The final allocation had to meet the maximum variance of the patient's arrival rates while still yielding results close to good welfare measures. The performance of the proposed model was evaluated according to the settings of a real hospital. Xu and Liu investigated the impact of resource under-investment on urban public healthcare service inequalities and produced an allocation method to maximize populations' average accessibility to healthcare services. Although basic medical resources were first considered, the model was applied to assess the spatial justice of comprehensive medical resources of patient traffic to health resources.

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Obtaining data and resources: The data used to design and test the model developed in this paper was obtained from a real smart hospital via simulated patients. This information consisted of historical attendance rates for health resource allocations across separate effective hours. To the best of the authors' knowledge, such an effort is unmatched in the literature analyzed. With this work, it is possible to comply with one of the most difficult challenges reported for building AI healthcare models: getting large datasets from healthcare settings where research and healthcare operations might collide at any access level. The inputs required expressed both the initial and target allocations in terms of percentage of effective hours.

VIII. FUTURE DIRECTIONS

Simply suggested, AI could use machine-learning-based classification algorithms, in combination with data pre-processing techniques, to identify healthcare process inefficiencies. Work processes, patients' and treatments' characteristics, etc. are included in time series data to analyze the hospitals' care processes. Potentially useful data sources are all hospital information systems from the emergency department up to in-patient unit care to the outpatient clinic area. A big part of the forecasting engine is that the attention will be shifted from a process-centered approach to an output-focused approach.

That is, the analysis would not rely on a forecasted plan but would use time series data describing real healthcare processes in order to identify targets of improvement or even to suggest improvement strategies. The AI engine would support two analysis processes: the chronic care pathway and resources characterization, and resources demand simulation and prognosis. The former would identify patients' chronic care pathways in order to characterize and classify them, while the latter would identify the resources used in chronic care path phases and would provide a forecast of their daily use.

Regarding healthcare staffing systems, AI could support the performance of informed and prudent human resource decisions, i.e., responsible recruitment, placement, and allocation. Automated staff planning and daily rescheduling would be based on a collection of available input data regarding supply and demand side resources and systematic forecast modeling of hospital-wide adjustments. The objective for the triage forecast system is to develop and put into practice models to understand how hospital admissions will be modified by the epidemic.

The challenge for the triage modeling is to overcome the changes in multimodality distribution and flow patterns over time, and to forecast a middle-term time horizon of up to 6 months due to uncertainties and variances. It is worth mentioning that this hospital has already been accepting patient transfers from other regions in the second wave, and similar cases are expected again in the future. High-preliminary and feedback-based queues and waiting-time forecasting would provide early warning of exceeding thresholds and start, promptly, countermeasures in order to find opportunities for savings. Additional high-preliminary estimate queue monitoring could address primary processing queues before and in front of the examination rooms, follow-up queue monitoring at the radiology department, and observation of instrument processing capacity.

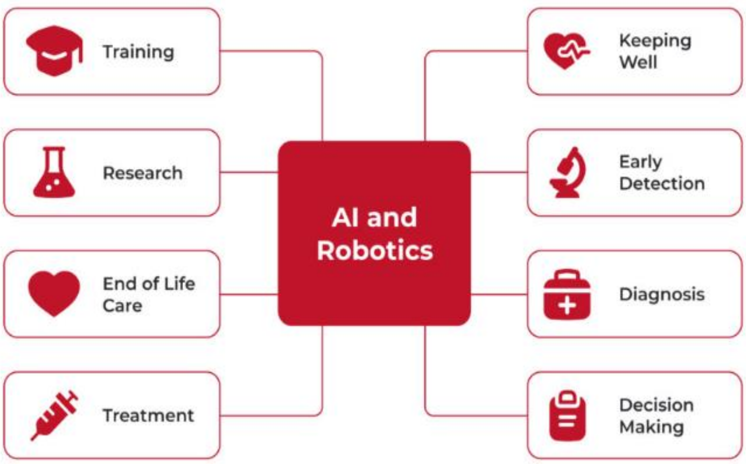

Fig 5: AI Future in Healthcare

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8.1. Emerging Technologies

Diverse technologies comprise enabling technologies first relied on to improve overall contextual conditions for the design of novel and effective operations. After that, enhancing technologies are amalgamated to build new and advanced systems, tools, and techniques. Finally, controlling technologies, such as information and communication technology, modeling and optimization technology, and advanced AI techniques, are adopted to build smart and advanced operations. Nowadays, several emerging technologies have advanced and are now in the early phase of being implemented in many conventional operations. On the one hand, these technologies will not only broaden the boundaries of the feasible solutions for new designs of operations but they will also substantially disrupt and revolutionize many traditional and widely used methods, systems, and even business models.

Large amounts of data are generated from daily operations and processes for decision-making purposes in diverse applications. They include features seen by humans as operational entities, such as situations, objects, or time-varying variables. In the conventional business intelligence culture, the collected data are transformed to create information by explicitly analyzing and processing for recognitions, understandings, and insights. Important decisions can then be made accordingly. A strong limitation of this culture is that operations must generate features understood by human experts to analyze and process, which is often demanding and usually impossible.

With the rapid progress in big data technology, with advanced tools and techniques such as wide-ranging monitoring sensors, massively parallel high-performance computing resources, and cloud platforms, there is an urgent opportunity to automatically acquire fresh data directly from operations for analytics. Operations have emerged as complex networks of interrelated constituents, including humans, machines, companies, and organizations. Hence, they become operations-based dynamic systems concerning the states, behaviors, and conditions rather than the traditional data-based stateless entities. Mining the features of these complex network systems, which appear by self-determined mathematical and computational descriptions (or models), serves as a recently emerging paradigm for automatic data and information processing in diverse industrial applications.

8.2. Potential Research Areas

Several avenues for future research exist. First, the approach proposed in this research has focused on predicting admissions for the following day. In cases where cloud processing is available, a broader forecast horizon could be used. Instead of producing one-day-ahead predictions, it is possible to forecast multiple days or even weeks ahead. One possible approach for this is to apply probabilistic models to obtain an estimated probability density function of the demand instead of a single point prediction. Furthermore, depending on the forecast horizon, other constraints should also be taken into consideration. For instance, it is possible that on holidays, patients' arrival can be affected in a different way than a normal day, resulting in an imbalance in resource allocation if only one day ahead is naively considered.

Second, an important contribution is the resource allocation method. In the current development, generic length-of-stays are assigned to triage groups. Having a mechanism to dynamically update length-of-stay parameters as training data occurs is interesting. Furthermore, recently, methods such as deep reinforcement learning have become more popular. Reinforcement learning methods have been used for resource allocation. In this research work, the resource planner is fully centralized. It is possible to distribute the optimizer and parallelize it among servers, which allows optimization to be running in a real-time sense. A decentralized reinforcement learning method can be developed, where agents can interact with environments independently.

Third, the cloud application is highly extensible. It is possible to expand the current configuration to include additional but appropriate comments while following the multi-agent methods. In particular, in real-life optimization agent design, cloud platforms can be used to collaborate. Multiple cloud providers can work together to go to a thought-leader to formulate the competition rules. Multiple agents can play against each other and provide appropriate comments.

8.3. Policy Implications

This paper presents an AI-assisted flexible cloud-based resource management platform that provides data analytics and predictive modeling for resource management in the healthcare industry, specifically hot hospitals. The three key components of this platform are also described. Their technical architecture, data analytics methodologies, and algorithmic details are presented. To evaluate the effectiveness of AI technology for healthcare resource analytics, a resource management dashboard has been developed and implemented for use in hospitals across the United States. Limitations and future work in the AI-assisted flexible resource management platform are also discussed.

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Nursing shortages in hospitals have been accelerated due to the COVID-19 pandemic and are projected to continue in the long term. Hospitals are incentivized to use resources effectively to protect patient safety and increase hospital revenues. However, many hospitals do not have an adequate ability to identify excess resources that could be used in other locations. Many healthcare providers also lack an adequate ability to assess, prioritize, and balance competing resource needs under budget constraints. Big data and AI technologies are proposed to provide a flexible cloud-based supply chain resource management platform to advance knowledge in healthcare operations, improve labor supply chain outcomes, and prepare for a post-pandemic era.

To address nursing shortages, a flexible cloud-based resource management platform using AI technologies is presented. The components of the platform include a dashboard based on RL, a binary GA bidding model, and a TSP model based on GA. Findings highlight the effectiveness of the AI-assisted resource management platform in improving decision quality and operational efficiency and the practicality of these models as an executive decision support tool. Detailed methodology for platform implementation, case studies of the empirical application of the dashboard, and preliminary results from hospitals in the United States are provided.

Due to the COVID-19 pandemic, hospitals with a focus on intensive patient care are experiencing large shifts in predictable demand. Dealing with these fluctuations is difficult for hospitals but it is essential for safety and resource allocation issues. Winter discharges can be informed by publicly available bed and discharge data. Specific techniques and available data are given that can aid hospitals in assessing their ability to accommodate new patients. Solutions can then be formed proactively by utilizing optimization methods or algorithms that could facilitate bed assignment and transfers. In addition to improving the utilization of healthcare resources, these techniques could also be useful for addressing staffing shortages and optimizing patient scheduling. There is a need for large-scale data sharing within and between providers. Such sharing would require security and protection. The cost is bound to be minimal when weighed against the improvement in patient care that could be achieved.

IX. CONCLUSION

"…The hospital admitted 104 pandemic patients over two months, far exceeding the 6-month projection of 104 anticipated admissions. Six hundred seventy-five patients were excluded by the prioritization model prior to admission, leaving additional care gaps of overcrowding. Disparities in healthcare access for asian patients were noted, despite prior adjustments for age and income. The negative residual effect of Covid-19 not addressed by the models was shown…". Such effects were observed in other economically advanced regions of the world, as well as in developing countries. Unable to allocate similar amounts of resources to hospitals inadequate in size or funding, such inequalities were exacerbated.The comprehensive resource management R dashboard using Reinforcement Learning can help hospital administrations know whether they have additional resources that they may be able to share with others. The binary Genetic Algorithm model for case-load day percentage allocation of the rough resource availability based on a trained percentage value can provide administrators unbiased information to suggest whether the hospital should receive

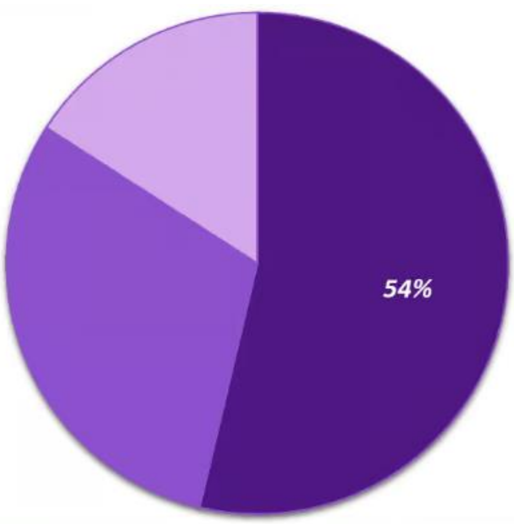

Fig 6: AI in healthcare operations:optimizing hospital resource allocation.

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Despite treatment of the feeble elderly, mortality rates soared. Conversely, in other areas of the world, including developing countries, well-structured operational procedures and timely treatment resulted in successful outcomes. Time-sensitive economic opportunities also arose. Medical providers had advance notice to procure sought-after samples. Prescient investors early placed vaccine orders. Advanced rollouts ensued within economic systems, ushering in longer-term market dominance. The use of COVID-19 as a competitive economic weapon muffled compliant nations in fear of outbreaks. Surprise announcements of negative effects, tampering accusations, and unplanned suspect departures of key players planted suspicions or doubts. Non-competing groupings lobbied for recourse, with some inventing new and advanced agents.

Resource Allocation protocols were put in place to avoid scrambling decisions due to shortages of material or workforce during such events. “Default Entry Protocols” even were designed for quick reactive setup for net-new or less-involved entrants. How an institution adapted rules for COVID-19 cases would reveal resource gaps, request unwarranted values, and even cause public concern about inequities of healthcare access.

Additional resources or not. Finally, the Travelling Salesman Problem with GA can provide unbiased route suggestions based on cost, emergency, distance, and other factors. These models can be used together or independently during outlier events at the discretion of hospital management as suited.

REFERENCES

[1] Kommaragiri, V. B., Preethish Nanan, B., Annapareddy, V. N., Gadi, A. L., & Kalisetty, S. (2022). Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing. Venkata Narasareddy and Gadi, Anil Lokesh and Kalisetty, Srinivas.

[2] Pamisetty, V., Dodda, A., Singireddy, J., & Challa, K. (2022). Optimizing Digital Finance and Regulatory Systems Through Intelligent Automation, Secure Data Architectures, and Advanced Analytical Technologies. Jeevani and Challa, Kishore, Optimizing Digital Finance and Regulatory Systems Through Intelligent Automation, Secure Data Architectures, and Advanced Analytical Technologies (December 10, 2022).

[3] Paleti, S. (2022). The Role of Artificial Intelligence in Strengthening Risk Compliance and Driving Financial Innovation in Banking. International Journal of Science and Research (IJSR), 11(12), 1424–1440. https://doi.org/10.21275/sr22123165037

[4] Komaragiri, V. B. (2022). Expanding Telecom Network Range using Intelligent Routing and Cloud-Enabled Infrastructure. International Journal of Scientific Research and Modern Technology, 120–137. https://doi.org/10.38124/ijsrmt.v1i12.490

[5] Pamisetty, A., Sriram, H. K., Malempati, M., Challa, S. R., & Mashetty, S. (2022). AI-Driven Optimization of Intelligent Supply Chains and Payment Systems: Enhancing Security, Tax Compliance, and Audit Efficiency in Financial Operations. Tax Compliance, and Audit Efficiency in Financial Operations (December 15, 2022).

[6] Mashetty, S. (2022). Innovations In Mortgage-Backed Security Analytics: A Patent-Based Technology Review. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3826

[7] Kurdish Studies. (n.d.). Green Publication. https://doi.org/10.53555/ks.v10i2.3785

[8] Motamary, S. (2022). Enabling Zero-Touch Operations in Telecom: The Convergence of Agentic AI and Advanced DevOps for OSS/BSS Ecosystems. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3833

[9] Kannan, S. (2022). AI-Powered Agricultural Equipment: Enhancing Precision Farming Through Big Data and Cloud Computing. Available at SSRN 5244931.

[10] Suura, S. R. (2022). Advancing Reproductive and Organ Health Management through cell-free DNA Testing and Machine Learning. International Journal of Scientific Research and Modern Technology, 43–58. https://doi.org/10.38124/ijsrmt.v1i12.454

[11] Nuka, S. T., Annapareddy, V. N., Koppolu, H. K. R., & Kannan, S. (2021). Advancements in Smart Medical and Industrial Devices: Enhancing Efficiency and Connectivity with High-Speed Telecom Networks. Open Journal of Medical Sciences, 1(1), 55-72.

[12] Meda, R. (2022). Integrating IoT and Big Data Analytics for Smart Paint Manufacturing Facilities. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3842

[13] Annapareddy, V. N., Preethish Nanan, B., Kommaragiri, V. B., Gadi, A. L., & Kalisetty, S. (2022). Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing. Venkata Bhardwaj and Gadi, Anil Lokesh and Kalisetty, Srinivas, Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing (December 15, 2022).

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022
DOI: 10.17148/IJIREEICE.2022.101215

[14] Phanish Lakkarasu. (2022). AI-Driven Data Engineering: Automating Data Quality, Lineage, And Transformation In Cloud-Scale Platforms. Migration Letters, 19(S8), 2046–2068. Retrieved from https://migrationletters.com/index.php/ml/article/view/11875
[15] Kaulwar, P. K. (2022). Securing The Neural Ledger: Deep Learning Approaches For Fraud Detection And Data Integrity In Tax Advisory Systems. Migration Letters, 19, 1987-2008.
[16] Malempati, M. (2022). Transforming Payment Ecosystems Through The Synergy Of Artificial Intelligence, Big Data Technologies, And Predictive Financial Modeling. Big Data Technologies, And Predictive Financial Modeling (November 07, 2022).
[17] Recharla, M., & Chitta, S. (2022). Cloud-Based Data Integration and Machine Learning Applications in Biopharmaceutical Supply Chain Optimization.
[18] Lahari Pandiri. (2022). Advanced Umbrella Insurance Risk Aggregation Using Machine Learning. Migration Letters, 19(S8), 2069–2083. Retrieved from https://migrationletters.com/index.php/ml/article/view/11881
[19] Paleti, S., Burugulla, J. K. R., Pandiri, L., Pamisetty, V., & Challa, K. (2022). Optimizing Digital Payment Ecosystems: Ai-Enabled Risk Management, Regulatory Compliance, And Innovation In Financial Services. Regulatory Compliance, And Innovation In Financial Services (June 15, 2022).
[20] Singireddy, J. (2022). Leveraging Artificial Intelligence and Machine Learning for Enhancing Automated Financial Advisory Systems: A Study on AIDriven Personalized Financial Planning and Credit Monitoring. Mathematical Statistician and Engineering Applications, 71 (4), 16711–16728.
[21] Paleti, S., Singireddy, J., Dodda, A., Burugulla, J. K. R., & Challa, K. (2021). Innovative Financial Technologies: Strengthening Compliance, Secure Transactions, and Intelligent Advisory Systems Through AI-Driven Automation and Scalable Data Architectures. Secure Transactions, and Intelligent Advisory Systems Through AI-Driven Automation and Scalable Data Architectures (December 27, 2021).
[22] Sriram, H. K. (2022). Integrating generative AI into financial reporting systems for automated insights and decision support. Available at SSRN 5232395.
[23] Koppolu, H. K. R. (2021). Leveraging 5G Services for Next-Generation Telecom and Media Innovation. International Journal of Scientific Research and Modern Technology, 89–106. https://doi.org/10.38124/ijsrmt.v1i12.472
[24] End-to-End Traceability and Defect Prediction in Automotive Production Using Blockchain and Machine Learning. (2022). International Journal of Engineering and Computer Science, 11(12), 25711-25732. https://doi.org/10.18535/ijecs.v11i12.4746
[25] Chaitran Chakilam. (2022). AI-Driven Insights In Disease Prediction And Prevention: The Role Of Cloud Computing In Scalable Healthcare Delivery. Migration Letters, 19(S8), 2105–2123. Retrieved from https://migrationletters.com/index.php/ml/article/view/11883
[26] Sriram, H. K., ADUSUPALLI, B., & Malempati, M. (2021). Revolutionizing Risk Assessment and Financial Ecosystems with Smart Automation, Secure Digital Solutions, and Advanced Analytical Frameworks.
[27] Avinash Pamisetty. (2021). A comparative study of cloud platforms for scalable infrastructure in food distribution supply chains. Journal of International Crisis and Risk Communication Research , 68–86. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2980
[28] Gadi, A. L., Kannan, S., Nanan, B. P., Komaragiri, V. B., & Singireddy, S. (2021). Advanced Computational Technologies in Vehicle Production, Digital Connectivity, and Sustainable Transportation: Innovations in Intelligent Systems, Eco-Friendly Manufacturing, and Financial Optimization. Universal Journal of Finance and Economics, 1(1), 87-100.
[29] Dodda, A. (2022). The Role of Generative AI in Enhancing Customer Experience and Risk Management in Credit Card Services. International Journal of Scientific Research and Modern Technology, 138–154. https://doi.org/10.38124/ijsrmt.v1i12.491
[30] Gadi, A. L. (2022). Connected Financial Services in the Automotive Industry: AI-Powered Risk Assessment and Fraud Prevention. Journal of International Crisis and Risk Communication Research, 11-28.
[31] Pamisetty, A. (2022). A Comparative Study of AWS, Azure, and GCP for Scalable Big Data Solutions in Wholesale Product Distribution. International Journal of Scientific Research and Modern Technology, 71–88. https://doi.org/10.38124/ijsrmt.v1i12.466
[32] Adusupalli, B. (2021). Multi-Agent Advisory Networks: Redefining Insurance Consulting with Collaborative Agentic AI Systems. Journal of International Crisis and Risk Communication Research, 45-67.
[33] Dwaraka Nath Kummari. (2022). Iot-Enabled Additive Manufacturing: Improving Prototyping Speed And Customization In The Automotive Sector . Migration Letters, 19(S8), 2084–2104. Retrieved from https://migrationletters.com/index.php/ml/article/view/11882
[34] Data-Driven Strategies for Optimizing Customer Journeys Across Telecom and Healthcare Industries. (2021). International Journal of Engineering and Computer Science, 10(12), 25552-25571. https://doi.org/10.18535/ijecs.v10i12.4662

DOI: 10.17148/IJIREEICE.2022.101215

[35] Adusupalli, B., Singireddy, S., Sriram, H. K., Kaulwar, P. K., & Malempati, M. (2021). Revolutionizing Risk Assessment and Financial Ecosystems with Smart Automation, Secure Digital Solutions, and Advanced Analytical Frameworks. Universal Journal of Finance and Economics, 1(1), 101-122.

[36] AI-Based Financial Advisory Systems: Revolutionizing Personalized Investment Strategies. (2021). International Journal of Engineering and Computer Science, 10(12). https://doi.org/10.18535/ijecs.v10i12.4655

[37] Karthik Chava. (2022). Harnessing Artificial Intelligence and Big Data for Transformative Healthcare Delivery. International Journal on Recent and Innovation Trends in Computing and Communication, 10(12), 502–520. Retrieved from https://ijritcc.org/index.php/ijritcc/article/view/11583

[38] Challa, K. (2022). The Future of Cashless Economies Through Big Data Analytics in Payment Systems. International Journal of Scientific Research and Modern Technology, 60–70. https://doi.org/10.38124/ijsrmt.v1i12.467

[39] Pamisetty, V., Pandiri, L., Annapareddy, V. N., & Sriram, H. K. (2022). Leveraging AI, Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management. Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management (June 15, 2022).

[40] Innovations in Spinal Muscular Atrophy: From Gene Therapy to Disease-Modifying Treatments. (2021). International Journal of Engineering and Computer Science, 10(12), 25531-25551. https://doi.org/10.18535/ijecs.v10i12.4659

[41] Kaulwar, P. K. (2022). Data-Engineered Intelligence: An AI-Driven Framework for Scalable and Compliant Tax Consulting Ecosystems. Kurdish Studies, 10 (2), 774–788.

[42] Operationalizing Intelligence: A Unified Approach to MLOps and Scalable AI Workflows in Hybrid Cloud Environments. (2022). International Journal of Engineering and Computer Science, 11(12), 25691-25710. https://doi.org/10.18535/ijecs.v11i12.4743

[43] Nandan, B. P., & Chitta, S. (2022). Advanced Optical Proximity Correction (OPC) Techniques in Computational Lithography: Addressing the Challenges of Pattern Fidelity and Edge Placement Error. Global Journal of Medical Case Reports, 2(1), 58-75.

[44] Raviteja Meda. (2021). Machine Learning-Based Color Recommendation Engines for Enhanced Customer Personalization. Journal of International Crisis and Risk Communication Research , 124–140. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/3018

[45] Rao Suura, S. (2021). Personalized Health Care Decisions Powered By Big Data And Generative Artificial Intelligence In Genomic Diagnostics. Journal of Survey in Fisheries Sciences. https://doi.org/10.53555/sfs.v7i3.3558

[46] Implementing Infrastructure-as-Code for Telecom Networks: Challenges and Best Practices for Scalable Service Orchestration. (2021). International Journal of Engineering and Computer Science, 10(12), 25631-25650. https://doi.org/10.18535/ijecs.v10i12.4671

[47] Vamsee Pamisetty, Lahari Pandiri, Sneha Singireddy, Venkata Narasareddy Annapareddy, Harish Kumar Sriram. (2022). Leveraging AI, Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management. Migration Letters, 19(S5), 1770–1784. Retrieved from https://migrationletters.com/index.php/ml/article/view/11808

[48] Someshwar Mashetty. (2020). Affordable Housing Through Smart Mortgage Financing: Technology, Analytics, And Innovation. International Journal on Recent and Innovation Trends in Computing and Communication, 8(12), 99–110. Retrieved from https://ijritcc.org/index.php/ijritcc/article/view/11581

[49] Srinivasa Rao Challa,. (2022). Cloud-Powered Financial Intelligence: Integrating AI and Big Data for Smarter Wealth Management Solutions. Mathematical Statistician and Engineering Applications, 71(4), 16842–16862. Retrieved from https://philstat.org/index.php/MSEA/article/view/2977

[50] Paleti, S. (2022). Fusion Bank: Integrating AI-Driven Financial Innovations with Risk-Aware Data Engineering in Modern Banking. Mathematical Statistician and Engineering Applications, 71(4), 16785-16800.

[51] Pamisetty, V. (2022). Transforming Fiscal Impact Analysis with AI, Big Data, and Cloud Computing: A Framework for Modern Public Sector Finance. Big Data, and Cloud Computing: A Framework for Modern Public Sector Finance (November 30, 2022).

[52] Kommaragiri, V. B., Gadi, A. L., Kannan, S., & Preethish Nanan, B. (2021). Advanced Computational Technologies in Vehicle Production, Digital Connectivity, and Sustainable Transportation: Innovations in Intelligent Systems, Eco-Friendly Manufacturing, and Financial Optimization.

[53] Annapareddy, V. N. (2022). Integrating AI, Machine Learning, and Cloud Computing to Drive Innovation in Renewable Energy Systems and Education Technology Solutions. Available at SSRN 5240116.

[54] Transforming Renewable Energy and Educational Technologies Through AI, Machine Learning, Big Data Analytics, and Cloud-Based IT Integrations. (2021). International Journal of Engineering and Computer Science, 10(12), 25572-25585. https://doi.org/10.18535/ijecs.v10i12.4665

DOI: 10.17148/IJIREEICE.2022.101215

[55] Venkata Bhardwaj Komaragiri. (2021). Machine Learning Models for Predictive Maintenance and Performance Optimization in Telecom Infrastructure. Journal of International Crisis and Risk Communication Research , 141–167. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/3019

[56] Paleti, S. (2021). Cognitive Core Banking: A Data-Engineered, AI-Infused Architecture for Proactive Risk Compliance Management. AI-Infused Architecture for Proactive Risk Compliance Management (December 21, 2021).

[57] Harish Kumar Sriram. (2022). AI-Driven Optimization of Intelligent Supply Chains and Payment Systems: Enhancing Security, Tax Compliance, and Audit Efficiency in Financial Operations. Mathematical Statistician and Engineering Applications, 71(4), 16729–16748. Retrieved from https://philstat.org/index.php/MSEA/article/view/2966

[58] Chava, K., Chakilam, C., Suura, S. R., & Recharla, M. (2021). Advancing Healthcare Innovation in 2021: Integrating AI, Digital Health Technologies, and Precision Medicine for Improved Patient Outcomes. Global Journal of Medical Case Reports, 1(1), 29-41.

[59] Data Engineering Architectures for Real-Time Quality Monitoring in Paint Production Lines. (2020). International Journal of Engineering and Computer Science, 9(12), 25289-25303. https://doi.org/10.18535/ijecs.v9i12.4587

[60] Pallav Kumar Kaulwar. (2021). From Code to Counsel: Deep Learning and Data Engineering Synergy for Intelligent Tax Strategy Generation. Journal of International Crisis and Risk Communication Research , 1–20. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2967

[61] Pandiri, L., & Chitta, S. (2022). Leveraging AI and Big Data for Real-Time Risk Profiling and Claims Processing: A Case Study on Usage-Based Auto Insurance. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3760

[62] Kummari, D. N. (2022). AI-Driven Predictive Maintenance for Industrial Robots in Automotive Manufacturing: A Case Study. International Journal of Scientific Research and Modern Technology, 107–119. https://doi.org/10.38124/ijsrmt.v1i12.489

[63] Gadi, A. L. (2022). Cloud-Native Data Governance for Next-Generation Automotive Manufacturing: Securing, Managing, and Optimizing Big Data in AI-Driven Production Systems. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3758

[64] Dodda, A. (2022). Secure and Ethical Deployment of AI in Digital Payments: A Framework for the Future of Fintech. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3834

[65] Gadi, A. L. (2021). The Future of Automotive Mobility: Integrating Cloud-Based Connected Services for Sustainable and Autonomous Transportation. International Journal on Recent and Innovation Trends in Computing and Communication, 9(12), 179-187.

[66] Dodda, A. (2022). Strategic Financial Intelligence: Using Machine Learning to Inform Partnership Driven Growth in Global Payment Networks. International Journal of Scientific Research and Modern Technology, 1(12), 10-25.

[67] Just-in-Time Inventory Management Using Reinforcement Learning in Automotive Supply Chains. (2021). International Journal of Engineering and Computer Science, 10(12), 25586-25605. https://doi.org/10.18535/ijecs.v10i12.4666

[68] Srinivasa Rao Challa. (2021). From Data to Decisions: Leveraging Machine Learning and Cloud Computing in Modern Wealth Management. Journal of International Crisis and Risk Communication Research , 102–123. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/3017

[69] Kommaragiri, V. B. (2021). Enhancing Telecom Security Through Big Data Analytics and Cloud-Based Threat Intelligence. Available at SSRN 5240140.