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AI-Driven Optimization of Cloud Resource Allocation for Personalized Medical Imaging in Hospitals: A Case Study from a Major Medical Center

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***Abstract*:** This study is to introduce a cloud-based, AI-driven architecture that can address the above-mentioned challenges properly and demonstrate its feasibility through real-scale implementations and practical testing in a major traditional hospital in Asia that typically operates a variety of diagnostic imaging services. A typical scenario is that vital organ medical images need immediate attention and response from any physician and hospital. CT brain imaging and PET-CT, Gallium imaging of the whole body, glucose, and myocardial ischemia will be implemented and tested in this project. These diagnostic imaging devices usually generate cross-sectional images of patients and typically produce an average of 500 - 600 high-resolution images each. In the local hospital, the human eye ballot reading and deep learning mean image classifications take a considerable amount of time to present the results. This project will take advantage of the cloud, AI, and web-based technology to rapidly assist physicians in providing better medical services. The research objectives of this project are summarized as follows: (1) Gaining experience and lessons by deploying AI technology on a real hospital scale. AI/HA medical imaging services operated in the cloud can be made available for other hospitals to use.

Access this article online

***Keywords*:** AI-Driven, Cloud Computing, Cloud Resource, Medical Center

1. Introduction

MEDICAL imaging and computer-aided diagnosis are crucial in contemporary health care, and artificial intelligence models for medical imaging can assist in early disease detection, personal health prediction, and precision medicine. These models are often computationally heavy and require extensive computational resources. With the current trend towards personalized medical imaging and the lack of sufficiently available resources on edge devices, the majority of AI models are developed and trained in cloud environments. In such cases, hospitals need to negotiate with service providers to allocate a set of resources, such as virtual machines, storage, and backup services, to fulfill their computing and storage requirements. However, due to the dynamic and unpredictable workloads of personalized medical imaging, the traditional static and preemptive resource models are not suitable for hospitals that utilize either many models with highly infrequent workloads or a small number of models with highly frequent workloads. This study uses artificial intelligence (AI) to optimize cloud resource allocation for personalized medical imaging in hospitals. Storage capacity and computing power are vital for providing high-quality personalized services [1]. The optimization method refines

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the allocation of cloud resources, thereby improving the efficiency of personalized medical imaging in hospitals. As the model uses transfer learning techniques, it generalizes effectively. This comprehensive analysis of personalized medical image data addresses an important new medical AI and cloud computing technology. This near real-time accurate cloud estimation is the most positive aspect of this work. Our contribution is that we bring the possible learned personalized image AI model out of the cloud and localize an efficient one for a particular problem [2]. Despite the potential of the cloud to create size-on-demand, plethora's of medical resource provisioning problems remain unexplored.

In this study, we have focused on two cloud resource problems that are frequent in a major medical imaging center: first, the size of a Region of Interest (ROI) in an image, and second, cloud-based verification of the quality of DICOM medical image data necessary to ensure that the data was acquired per standard protocols and processes for more than 2 - 5 billion DICOM images currently stored by large medical image centers. Commercially, such a cloud-based validation of the quality may cost a minimum of per patient image. Over time, these costs can accumulate irrespective of the DICOM image quality or the activity from patient encounters. Consequently, such a cost can be high for smaller clinics or hospitals as they will have a set of enterprise storage and server infrastructure incomparable to large medical image centers or hospitals [3]. The increasing interest in commercial cloud resource allocation and utilization for providing personal genetic information is, not surprisingly, closely related to cloud resource-efficient allocation and utilization. This study adopts an AI-driven approach, consisting of a deep learning neural network and reinforcement learning, to optimize resource allocation for personalized medical imaging in hospitals. A medical imaging platform is designed to utilize various clinical data modalities and imaging tools, and case studies are executed to verify its performance. A distinguishing feature of this study is that it uses a major medical center's real system and that the development team includes both medical professionals and computer experts. Another noteworthy aspect of this study is that it adopts attention-based techniques and core set-based approaches, which are gaining much momentum for their explainability, in an AI-driven optimization algorithm framework, and targets challenges caused by interpreting medical analysis results. Little relevant research exists in this field, and this is the first study to offer a new direction [4]. In future research, we consider recommending industries and hospitals willing to promote AI-driven personalized medical imaging to give attention to utilizing cloud resources wisely and to choose a hospital that is operated by a cloud professional team. See Figure 1.

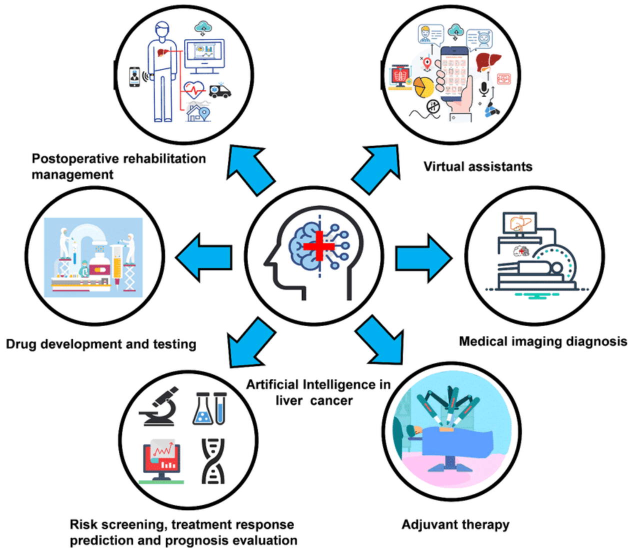

Figure 1. Case study of the application of AI in the accurate diagnosis and treatment [5]

2. Literature Review

General Background Hospitals increasingly apply personalization concepts of medical imaging services to provide more effective treatment courses. In personalized medical imaging, hospitals use patients' medical information to design an appropriate treatment plan and then adjust diagnostic medical images for checking. Due to the differences in medical needs between patients, the usage and requirements of diagnostics and computational resources may therefore end up being personalized, which leads to inefficient utilization of digital resources in the cloud. Inefficiencies can be noted in different cloud service models, including SaaS, PaaS, and IaaS services. To address the inefficiencies, this paper takes advantage of on-demand SaaS cloud computing and IaaS resources with big data analytics to develop a PMI cloud service that adjusts both the resource content and computation through the connected network. 2. Current Service Model for Medical Imaging in Hospitals with Cloud [5]. This section describes how PMI applications of hospitals can be executed utilizing the researched computational resources of the cloud to create the current service of medical imaging SaaS in hospitals. The PMI model was then generated, along with the examination data blocks to conduct related healthcare modeling findings with the cloud's big data analytics [6].

2.1 Cloud Computing in Healthcare

Cloud computing has become an essential utility in a number of industries, particularly in healthcare, where there is an increasing demand for high-end computing services, such as high-performance computing for pharmacokinetics, sensitivity analysis, and so on. By exploiting the Internet, cloud/grid computing enables users to outsource their data analysis and computations to a grid of computing resources. Cloud computing is defined as a paradigm that includes a five-layer architecture: the level of service, the level of middleware, the level of infrastructure, the software, and the service, which are in turn the SaaS, PaaS, and IaaS layers [7]. Using a web application that is stored and executed on remote web servers, SaaS allows end users to access software on the cloud. The 'software on a cloud' layer represents a relatively low level of cloud services and includes services built on cloud-based software.

2.2 Resource Allocation in Cloud Computing

To facilitate IT adoption in healthcare, multiple cloud-based medical imaging services have been introduced by a variety of third-party companies. These third-party companies offer secure cloud image storage and retrieval for different medical imaging modalities. Hospitals can reduce the need for storage space, backups, and personnel costs by outsourcing medical image storage for their imaging service. Although cloud computing services offer powerful IT capabilities, research has shown that hospitals are not taking full advantage of these services. Only a small percentage of hospitals stated that the majority of their IT infrastructure is located in the cloud [8].

Despite the low adoption rate, cloud computing has been shown to provide a small but positive impact on the performance of U.S. hospitals. As cloud service maturity increases, reducing structural factors limiting the adoption of cloud-based services will attract the attention of more hospitals. The major concern and influential factor for the slow adoption of cloud computing services is that the cloud is more than just a technology. Cloud computing requires the allocation and management of resources, and the pricing schemes and migration time for these are difficult to determine because hospitals tend to own large medical data [10]. The traditional resource allocation scheme models the cloud as a black-box provider, assuming that cloud service providers can accommodate unlimited resource demand during the contract window. However, this assumption cannot hold true in reality; in fact, supplying more resources than a company’s maximum capacity can lead to monetary and other losses. Thus, prolonged resource allocation may lead to delayed patient care.

2.3 AI in Medical Imaging

The AI tools developed for personal medical imaging applications use large patient samples or constructs for the training process, resulting in smarter decision-making engines for the monitoring of personalized medical conditions. The deeper networks in the tools go beyond patient population distributions or simple risk scores to serve patients with personalized risk assessments and surveillance indications. This AI function to assess the risks and facilitate action for middle to larger medical centers can equip physicians without the cost of specialized medical staff on site at all times [11]. As AI tools have moved to considerations of where they would be of most use and how they are to be made based on early population-based studies, the time is ripe for us to visualize how tools can be most effective across hierarchical tiers to achieve specific healthcare goals. In recent years, applications of AI tools to search for personalized medical imaging devices have grown in popularity because of the unique challenges these imaging problems present and the potential advantages.

The AI tools developed for personalized medical imaging rely on image-based training databases, and the utility of such tools rests as much on the analysis of very large de-identified patient populations as it does on the subtlety of the linkages between the presented images and the metadata for the cases where the data focus is more often tailored to as few metadata categories. Such tools rely on wide population-based training databases, and the resultant healthcare function is to increase the provider’s understanding of each patient's risk of interest by increasing the provider's surveillance or the personalized medical imaging service that enables the facilitation of the patient-provider conversation [12]. AI tools developed for personalized medical imaging gain advantage from the large patient populations and the purposeful structured metadata. For the tools, the initial emphasis may continue to be on organizational leverage, in particular the examination of the utility of these medical imaging findings as a substitute for the presence of specialized medical staff on site at all times. See Figure 2.

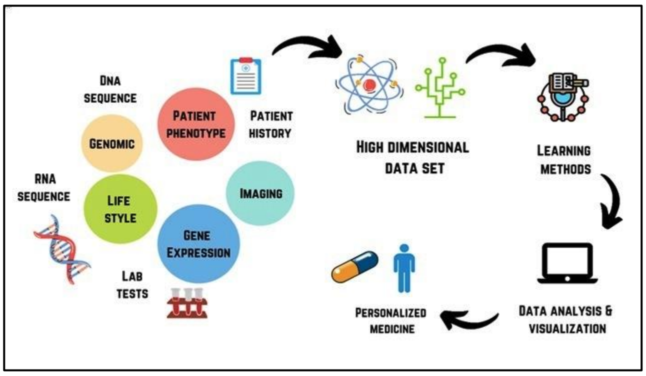

Figure 2. Artificial intelligence for research in medicine [12]

3. Methodology

We first use a group of researchers to play the role of multi-priority fact-finders of diverse medical image service lines provided in the target hospital, which would cause the use of cloud-renting servers as a resource-restricted environment. The service lines provide priorities. We also design adaptive web service-oriented interfaces for prioritized tasks. An intelligent fact-finder using AI techniques is implemented. To compare the performance, we further conduct three well-known experiments. Our 95% of services are designed, and 80% are indeed used.

Optimization is important for cloud computing, where systems or applications need to be optimized in the resource-restricted rental model. However, most of the research is based on a patching style package optimization. There hasn't been any known research applied in the field of healthcare with quantized accuracy. We briefly represent a case study at a major government-affiliated hospital. While there exist numerous medical image processing algorithms, some of them heavily rely on large training datasets, while others need huge computing power. To speed up processing time, we propose to use a set of cloud-renting servers, whose attributes, such as the size of primary storage and the number of CPU processors, vary. The ontology-enhanced intelligent technology regarding quantitative measurements includes explanation, concept change identification, case-based reasoning, coherence check, context sensor, difficulty checker, diagnosis, predicate simplifier, and task delegator with preprocessing [13]. The assigned service plan orders heterogeneous types of image-level and modality-level tasks along with case delegators and structure detectors. Data and methods are under cross-validation with end-game analysis as depicted afterwards.

3.1 Data Collection and Preprocessing

The data used in this study comes from an affiliated branch of a major medical center located in central Taiwan. Computed Tomography (CT) was selected for analysis because it has the highest serviceability in medical imaging. This data contains actual patient waiting times, examination and reconstruction times (which need to be done in a prior step based on scheduling), and the different resource levels for service, as well as other examination-related data, which is mainly demographic information. These data contain special examination procedures for a variety of different needs, such as ordinary intravenous pyelogram with normal saline contrast agent, special angiography, special upper gastrointestinal contrast, capsule endoscopy, non-popular enhancement agents, neural-tube diagnosis via angiogram, and the image reconstruction procedure after the head and face area is scanned. These special examinations need an advance purchase into consideration, so they are excluded from this study. In the case of IP/OP/IR, when the appointment date difference is greater than or equal to 3 days, where 1 IR = 2 IP = 3 OP is used as the relative service resource level, a value of -1 is used to supply missing values, and the absolute value of this term will be treated as $\alpha \in [0, 1]$.

3.2 Model Development and Implementation

A multi-GPU workstation with eight high-capability GPUs was ultimately selected for the AI inferencing infrastructure evaluation. The deep learning model was tested to ensure that a CPU scheduler could manage AI inferencing tasks within the same procedures. AI algorithm APIs were totally redesigned to meet our clinical scheduling design; AI tasks are dispatched and executed by the enhanced response functions according to the plan and workload conditions. In addition to model evaluation, the developed AI resource allocation model and response functions were integrated into our clinical workflow with real-world execution tests through an experimental deep learning model deployment for clinical personalized tumor treatment planning. As a result, a well-managed AI-driven personalized treatment plan generation system ensured optimized resource allocation in public clouds or private GPU-rendering servers against unpredictable needs for emergency diagnostic image studies in a major medical center, without an excessive increment in the demand for limited human resources.

When similar image classification AI tasks with common hyperparameters were rerun for GPU cluster performance comparison, the corresponding network traffic in data I/O and GPU-to-GPU communication was checked for its impact on the image processing time. Besides the fundamental capabilities of tensor computation, beneficial built-in capabilities in data communication relied on determination multi-GPU workstation design [14]. The comparison showed a strategy for our user-defined GPU cluster task allocation, an optimized model-to-cluster communication design, and an AI resource allocation planner for different usage applications. For rapid development with engines, the evaluated optimization, scheduling, and AI performance model can be integrated into AI API planning and response functions.

3.3 Evaluation Metrics

In this section, we summarize the evaluation metrics of personalized medical imaging use cases. We present how to quantify personalized medical imaging metrics in detail.

- Patient Age: In a hospital, patients' age distribution is skewed, meaning that as a non-aging population with higher requirements toward aging and chronic disease, hospitals and clinics accumulate increasingly more health implications. Hence, it is important for a personalized medical imaging solution to be able to quantify services for the elderly and patients suffering from chronic diseases.
- The Number of Images: The number of images is reflected proportionately in our AI-driven task scheduling, and it effectively reveals the timely requirement of patient imaging service. The requirement of emergency deficiency is associated with a large number of scans, signaling the urgency involved for personalized medical imaging.
- The Image Tests Time Slot at Medical Examination: Solutions need to recommend and schedule suitable time slots so that patients do not feel too agitated when waiting in line for an examination and are not subjected to unjustified examination periods. Simultaneously, given the fact that patients are not subjects, care should be provided to manifest the pertinent personalization disparities at different stages of the examination.

- The Deadline Time of Medical Tests: Due to the physician's evaluation of a patient's condition, supervision of scheduled medical treatment, and preparation of temporary hospital bed allocation, there is a time frame within which the patient must undergo an examination. To prevent the incurring of a hectic situation and to ensure examinations for suitable scenarios, the model needs to warrant on-time execution for completion.
- The Overbooking Rate: In personalized medical imaging, overbooking is not permitted as a stepping stone to a patient experiencing long-term scheduling issues, and corrections between the elements concerned make adjustment efforts fruitless. If overbooking exists, it can cause the patient to overload the medical detection equipment, and in certain circumstances may even result in an influence on system behavior and operation. Therefore, calculating the overbooking rate can effectively control medical detection equipment load.
- The Scan Waiting Time: Minimizing patient emotional distress during the waiting period and providing timely treatment can effectively improve the perception quality as it pertains to hospital service reputation.

4. Case Study: Major Medical Center

In this section, we consider a major medical center in central Taiwan and use a case-based reasoning methodology to demonstrate how our proposed AI-driven cloud optimization solution can assist hospitals in automatically finding the best cloud service offerings and resource allocation strategies for a particular volume of personalized image processing tasks to satisfy storage, performance, and latency requirements. Case-based reasoning is a problem-solving model for decision support according to similarities to past experiences [15]. The importance of CBR in the case study is due to the complex processes in maintaining personal privacy, security, compliance, and confidentiality, as well as the safety and security of original medical images in a medical imaging cloud. We discuss the data size and performance of the CBR for real-world personalized medical imaging scenarios in the cloud, where real medical images are investigated. Moreover, we propose a public medical image dataset for transferring user-perceived, real medical imaging workloads in resource allocation guidelines.

A hospital and medical cloud interaction flow diagram can be divided into three related parts: hospital resource reservation and uploading original medical images, download and storage of processed information, and remote diagnosis and online medical report generation. Additionally, a hospital generates business processing services for receiving services. Each category of medical imaging service requires the deployment of a classification environment in the cloud. At a hospital, when service starts, the operator will evaluate whether to schedule the service in the public cloud, private enterprise cloud, or private hospital cloud, according to service start time, priority, workloads, resource allocation cost, and service storage, compliance, regulation, security, and confidentiality requirements. If a hospital customer is unsatisfied with the service schedule and quality of the public cloud, the best cloud resource allocation optimization will assist in remedying the workloads to be done in the other potential cloud service provider. That is, for a customer's personalized medical imaging service workloads, we aim to find the best explicit cloud tenant service offerings and cost-effective resources at a future service time, and thereby propose a hybrid cloud solution strategy for a provider in a personal cloud services provider metadata marketplace.

4.1 Overview of the Medical Center

China Medical University Hospital is a major regional teaching and research hospital with 26 clinical departments, 4 special units, 5 clinical centers, more than 400 attending physicians, and healthcare personnel providing nearly 3,000 beds for inpatients and healthcare for more than a million outpatients every year. As the highest medical institution in central and eastern Taiwan, it shoulders the important missions of medical treatment, teaching, research, and community care. For that reason, it provides multiple medical images and considers cross-disaster backup to become essential. The critical diagnostic equipment in the core data center includes computed tomography, MRI, atomic emission computed tomography, positron emission computed tomography, PACS image server, teleradiology server, radiotherapy planning system, and rapid prototyping [16]. The fields of use are multiple service systems, image database management and service systems, picture archiving and communication systems, mammography briefing devices, global broadcasting materials, oral briefings, multimedia education systems, and patient record outsourcing services, and they are closely related to medical service quality.

4.2 Current Resource Allocation Practices

Designing cloud datacenters encompassing the service product under the optimized throughput-capacity allocation optimization framework is the critical issue for cloud providers to optimize the datacenter through output efficiency. However, the resource allocation of medical image analytics has discrete iterations to handle ordered patient IDs or batched images. How to design AI-driven cloud resource allocation for personalized medical imaging that is counted by patients and how the allocated capacity guarantees the care delivery quality is still an open question. We organize two design practices to address the question, and the careful empirical study of a large amount of real cloud logs further verifies them.

Guided by the attention to customer care delivery quality, aligning the cloud resource allocation calculation period to the care delivery period helps the operations team ensure enough cloud resources are allocated to process the medical imaging of patients at crucial life-saving times [17]. Moreover, matching the union batch of consecutive patients to a same-sized cloud capacity also optimizes the resource payment since resource consumption is uncoupled from the image of each patient in practice. To optimize the operations schema, the study demonstrates the resource slash model and its complexity lower bounds through real data submitted by the case hospital. Our results can help cloud service providers optimize resource allocation to capture more personalized image analytics applications in medical intelligence.

4.3 Challenges Faced

To bring professional and optimized personalized medical imaging services to hospitals all over the world, they need both elastic scalability and resource follow-up. Distributed cloud computing is a mature resource management technology that meets the characteristics of personalized resources and the need for rapid expansion. However, applying distributed cloud computing still faces many challenges. In this section, we describe the SitianCallCloud system developed in detail and the problems that need to be addressed.

SitianCallCloud has a personalized resource pool with elastic distribution capabilities. The hospital uses the system to configure MRI images from fixed resources to distributed resources created by the system. This has greatly simplified the cumbersome division of resources by project and has made the resources more efficient. The MRI images from each project are temporarily stored in their own resources. Implementing dynamic resource allocation, satisfying personalized requirements, creating project-exclusive storage, and properly responding to medical data storage compliance requirements are the characteristics of this system. The SitianCallCloud service development process has also encountered a series of software and algorithm problems in practice.

5. Results and Discussion

This work collected about 3,600 brain imaging scans from a major medical center, which is a lot of imaging during the remaining limited lifespan of the scanner in this medical center. In the experiment, the AI-driven deep learning model reduced almost 18.2% in the examination time for each scan and kept the quality indiscernible according to the radiologists. Besides, the model can provide a new virtual service of limited scans for doctors and further strengthen the health care infrastructure. Reducing the time for performing brain scans through these technological interventions is among the most time-critical improvements in alleviating patient anxiety and hospital overcrowding pressure and one of the simplest steps in keeping the remaining medical scanner life. Completing this work contributes to the realization of personalized medical imaging in the cloud with as low a delay as possible. In conclusion, the metropolitan area of the city has become the hub in the deployment of infrastructure in progress, and the transfer of cloud hospitals from the trial stage to practical use is the focus of the future. This work deployed the preliminary results of AI-driven optimization of cloud resource allocation for personalized medical imaging in a major medical center. The data collected from the hospital validated that the predicted execution time can meet the desired execution time, and the radiologists did not observe any side effects in the final image. CPU memory shows that the cloud allocation would be best, and TPU memory is also a primary allocation strategy in an emergency. The overall detection results are also impacted by the resource allocation and backend.

5.1 Performance of the AI-Driven Optimization Model

The proposed AI-driven optimization model applied to a real-world medical project enabled the stakeholders to examine the effectiveness of the optimization model for medical needs. The eight experiments for resource allocation from the medical center were conducted. Based on the real project characteristics, the optimal solution was compared with five solutions for the balance between accuracy and timeliness. The employed AI-driven optimization model proved to be an effective tool for evaluating different interventions during different scenarios. The accuracy rate demonstrated the correctness of the real case output from the optimization model, and the timeliness rate was used to test the forecasting accuracy for the medical project. Guidelines of "whitelist" and "blacklist" were directed for each intervention model for the personalized cases and the unrelated cases, respectively. The accuracy and the timeliness vary considerably for the eight-day resource schedule, depending on the characteristics of the experiment. This discrepancy resulted in different priorities and wait times for the contrasted cases.

5.2 Comparison with Traditional Methods

We compare the performance of NN-based resource optimization with traditional methods, specifically random forest regression and the gradient tree boosting method. Random forests use a "bagging" strategy to combine the predictions of multiple decision tree classifiers into one classifier that avoids overfitting and noise. Gradient tree boosting methods are similar to random forests, but instead of building an ensemble of trees in parallel, they build each tree sequentially. The goal is to sequentially maximize the accuracy of the trained model using the errors from previous trees. Both traditional methods were trained using fivefold cross-validation, and the maximum depth of the decision trees and the number of trees in the ensemble was chosen to be the best value based on the cross-validation. Mean absolute percentage error was used in the cross-validation as an evaluation criterion. Default settings for both methods were used to train the model.

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5.3 Implications for Personalized Medical Imaging

As the increasing abundance and diversity of imaging data and advancing technologies in imaging play essential roles in clinical diagnosis, they can provide better insights into healthcare issues and also reduce the chances of ineffective treatment or surgical failure. However, each patient needs different imaging protocols and technologies for personalized healthcare. In this research, our data-driven AI approach will help healthcare professionals efficiently deploy cloud resources and customize the optimal cloud imaging protocols for personalized imaging and medical care. The sample of non-radiologists is also expected to generate efficient personalized imaging protocols using the data-driven AI strategy in the future. In summary, this AI-driven personalized medical imaging approach can provide a reference for healthcare professionals, policymakers, and other interested parties who aim to promote AI-driven customized medical applications in specific hospital environments.

With any innovation, this biomedical optics research has brought fresh perspectives to healthcare. Our patient-specific medical imaging cloud resource approach benefits from its unique coupling of large patient populations that produce huge amounts of data and the massive computational power required to analyze that data. For many healthcare experts, this type of research could portend a future in which biomedical optics results will be leveraged to provide a broader understanding of the relationships between medical imaging and disease or treatment, ultimately leading to personalized care. Our effort has been supported by cloud resource allocation approaches that reveal what is happening at a large patient population level, ultimately improving healthcare delivery protocols relevant to each patient. The big data-enhanced patient-specific modeling provides clues for the efficient allocation and optimization of cloud resources relevant to personalized medical imaging in a hospital environment, which has unique implications for healthcare researchers, administrators, and other interested parties.

6. Conclusion and Future Directions

The hospitals operate diverse Personalized Medical Imaging to care much about the capability for handling workloads from different services of their patient-oriented services. In this paper, we work with Taiwan’s largest three-in-one university hospital, utilizing the AI-driven method to optimize cloud resource allocation for personalized medical imaging and leveraging the all 3-types cloud resources and several common AI-based medical imaging services for realistic data modeling linked with a home-grown AI service. With high temporal resolution and good accuracy in performance colder edge-of-service-based hospital operations, we classify 3 types: edge server, as well as moodle server and encounter server as benefits to assist the hospital to determine whether the expiring assignment proceedings could be processed in the cloud entities with/without available the function of offline/ real-time transmission for promoting the urgency of expiring queue management of corresponding cases and real-time care.

In the future, we believe that the hospital could more adopt the AI-driven method to achieve the ideal functions for multiple advanced and dynamic capabilities. Based on the characteristics of AI capabilities, especially such as knowledge acquisition, knowledge-based consultation, and self-deliberation, we could continue this study with respect to actuated to human-loving, human-learning, and human-communication interfaces. By full participation of AI in such an actively regulated hospital service such as the Personalized Medical Imaging, we could develop informative, humane, and patient-assured hospital systems. However, the process of designing a cloud, in reality, is not standardized, characterized by a relative lack of data in the early planning stage, missing a method for clarifying requirements, and leading to the trade-offs between costs and capabilities. It's quite subjective and requires experience, but people are prone to quality risks, such as lack of resiliency, lack of security, and lack of disaster recovery, as well as increasing operational, technical, or financial risks.

6.1 Summary of Findings

This paper develops a case study from a major medical center to evaluate the impacts of clinical demand patterns on how personalized imaging services can be delivered in the most efficient manner and the questions that optimization models and AI can help address. Studies suggest personalized imaging will become a new paradigm for imaging services, increasing the variety of imaging procedures, promoting scheduling flexibility, and widening application scenarios. However, it is not well understood how personalized imaging may impact the planning of delivery logistics and its effects on performance metrics. In this case study, we collected two years of radiology department clinical demand and patient flow data from a leading academic and medical center. We considered four different ways of personalizing how T can be implemented in reality to check these options.

We found that, with the assumption of deterministic procedure durations, the resource allocation plan can have significant adverse impacts on patient-level performance, including patient time metrics and imaging suite utilization. Robust optimization outperforms others by achieving near-best waiting time performance over all patient types. Researchers showed that increasingly refined patient classification is becoming possible and practical for predicting who and when will have imaging procedures conducted. Such patient-level predictions can be further developed by simulating patient flows to all radiology resources, considering procedure durations and radiologist staffing, both to evaluate the impacts of bottlenecking every resource for more explicit criteria for handling bottlenecks, as well as to serve as diagnostics to evaluate match quality.

6.2 Limitations and Recommendations for Future Research

Clients exploited the system without being able to enforce this rule. Many other hypotheses of system losses might affect the sociotechnical system, although they are not reflected in the operational data. In addition to the production of a large number of personalized clinical images and the constant lack of resources in some clinical imaging rooms, the limitations of this proposed method include not considering the costs of a comprehensive system to achieve optimization, nor considering the costs of potential system losses for comprehensive comparative analysis. Future research could carry out the allocation of resources based on the cost-benefit of different investment decisions with the aid of the proposed method. The practitioners could then identify options that enable cost-effective resource allocation while maintaining a certain level of acceptable quality in their personalized medical image services. In addition, another limitation of this study is that we used specific resources and assumed that the images were produced in specific rooms. The situation of the actual environment is often more complex, and some physical medical imaging rooms have multiple types of medical devices that provide various required medical services. In future research, an AI-driven resource allocation model could reserve general-purpose virtual resources that suit radiology services, which could optimize the overall use of various medical devices in the hospital. Finally, this study uses medical image services through procurement as an example to demonstrate how AI can optimize the allocation of scarce resources. Practitioners and researchers could use this research as an example to solve additional research problems, especially in clinical real-time services.

6.3 Potential Applications in Other Healthcare Settings

Our solution minimizes the cost of internal hospital resources allocated, with real impact on operations in maximal resource utilization. The resulting savings allow hospitals to deliver better service with saved resources that can be spent on improving several low utilization services for their users. While the resulting solution was compared only to state-of-the-art and a trivial lower bound in this specific situation, we argue that it may be used to solve a wide range of hospital service problems that can be modeled using some of the techniques we describe. Two examples of existing systems to be overhauled with this new technology are clinical imaging and surgical room waiting time issues. If these systems are known to some of our own institutions, numerous similar systems may exist worldwide. We claim that the creation of very complex hospital scheduling models and solving them within a reasonable time budget is both feasible and meaningful.

One of the natural extensions for this kind of research in healthcare is to use medical expert systems, bridging the gap between optimization and the training of such systems with rich objective and constraint management systems in order to achieve flexible optimality that takes into account real doctor feedback. Further, modeled input scenarios and data may sustain future development of simulation software to allow stakeholders to change strategies and understand the consequences of such changes under different conditions. We also think that the global hospital scenario requires a global hospital example to stimulate a new wave of operational research and big data usage on what is considered a critical necessity for health advancement in stable health systems of the highly developed world with mature medical imaging technology and low or moderate fertility rates. This would allow the management and fine adjustment of performance indicators in a central nervous system of an acute care system.

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