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A Literature Review of Service Capacity Planning for Medical Technology Department

Hongying Fei[1], Yiming Kang[1,*]

[1]College of Management, Shanghai University, 99 Shangda Road, Shanghai, China
[*]Corresponding author

Abstract: *Medical examination plays an important role in the health care service process, thus the quality of service capability planning in medical technology department has great impact on the quality of overall medical services. The purpose of this study is to explore the most recent development of service capacity planning for medical technology department by identifying and structuring essential factors for medical examination capacity management. After reviewing the existing research in healthcare service capacity planning based on the proposed review structure, discussion about possible research breakthrough points are summarized.*

Keywords: *Healthcare Service, Capacity Planning, Medical Technology Department, Literature Review*

1. Introduction

Capacity planning decision is important for any industry, especially for the healthcare industry. On the one hand, the demand for healthcare services is much greater than the existing capacity of the healthcare organization, on the other hand, the optimization of healthcare services involves the management of highly specialized and expensive resources (doctors, nurses and advanced medical equipment), and where capacity planning for healthcare services in crisis situations constantly has an impact on lives and deaths [1]. In many cases, the service capacity of a healthcare facility is a vague and difficult to measure concept that changes with local economic conditions and over time [2]. The limited capacity of all operations related to the performance of hospital health services in any hospital and the different nature of most scarce health care resources make it critical to determine the capacity or service capability of each of the different forms of resources in a hospital system.

Healthcare service capacity planning has been an area of adaptation and interest for many researchers. Healthcare optimization problems fall into two main categories: resource allocation problems and capacity design problems. The former focuses on how to allocate available capacity to accepted requests in order to optimize performance metrics, the latter attempts to determine the capacity required for healthcare services for a given level of arriving patient demand [3]. In healthcare, capacity planning is a planning approach to determine the required capacity for future arrival demand considering future demand for a specific service day.

In recent years, with the rapid development of modern medicine and science technology, medical technologies such as imaging, MRI technology and ultrasound sensing and other advanced technologies have become important tools in medical institutions for healthcare and treatment services. As an important part of medical institutions, Medical Technology Department (MT department) mainly examines patients' bodies through medical equipment and provides scientific basis for clinical diagnosis. Since medical examination services not only permeate all departments of medical institutions, but also run through the whole treatment process of patient consultation, treatment and rehabilitation. Therefore, the efficiency of MT department greatly affects the service efficiency and patient satisfaction. At present, the high level of patient demand and the shortage of medical resources make most of MT departments provide services by appointment, and with the special characteristics of "human-machine combined" medical examination service, the capacity of appointment determines to a certain extent the number of patients received and the waiting time of patients in the departments. The importance of effective management of capacity planning in MT department cannot be overstated.

In this paper, we first review the essential factors and characteristics related with healthcare service capacity planning, based on which we structure the literature review and propose future research directions for service capacity planning in medical technology department.

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2. Essential Factors involved in service capacity planning for MT department

As a tertiary industry, healthcare service has both the commonality and uniqueness of ordinary service industry. Most medical services vary from person to person and from disease to disease and require the collaborative participation of both medical institutions and patients. It is also difficult to standardize the indicators for measuring the capacity of medical institutions because of the different ways of departmental services and the resources required to provide healthcare services. In general, important indicators of healthcare service capacity are divided into factors involving patient demand and availability of healthcare service resources. The former is an indicator from the perspective of meeting patients' needs for medical care, such as the number of patients accepted, waiting time for medical care and patient satisfaction, while the latter indicates the availability of medical service resources such as beds, operating rooms, physicians and medical equipment, which more visually represents the service capacity of a medical institution.

The number of inpatient beds is one of the most basic measures of a hospital's capacity, and many hospitals even use inpatient beds as a reflection of their healthcare delivery capacity. In the past, foreign hospital bed capacity was determined by target occupancy rates; in recent years, a considerable body of literature has described the use of queuing theory, simulation and optimization models to support hospital inpatient bed planning problems. With the improvement of the healthcare delivery system and the development of Internet technology, the number of inpatient bed configurations is becoming more flexible, and the deployment of beds in different departments to optimize occupancy has become the focus of inpatient bed capacity planning.

Another important component of healthcare delivery capacity is human resources, especially nurses. In clinical departments, nurses are the main operators as well as service providers. On the one hand, nursing costs represent a relatively large part of hospital budgets, on the other hand, nursing has a significant impact on clinical outcomes [4], making the number of nurses an important object of optimization in the field of health care capacity planning. Although much has been written about the use of optimization models to determine nurse staffing, the underlying data required for such models are usually lacking.

Another significant component of the capacity planning is the operating room. With surgery as an important source of revenue for hospitals, efficient utilization of the operating room is critical to health care delivery capacity planning. Work addressing the issue of OR scheduling was once a major focus in the health care optimization literature.

In addition, with the rapid advancement of medical technology, medical diagnostic equipment such as MRI equipment and CT equipment have become emerging capacity categories. The price and the maintenance cost of medical diagnostic equipment are very expensive, and medical technology examinations that rely on medical equipment not only permeate all departments of medical institutions, but also run through the entire treatment process of patient consultation, treatment and rehabilitation, so medical equipment capacity allocation is also an important part of medical service capacity planning in order to avoid medical equipment capacity processes and low utilization. Medical examination equipment is not only an important asset of medical institutions, but also a huge cost source. The single-minded pursuit of maximizing the capacity of examination equipment will make the equipment work in a highly busy state for a long time, and the risk of random failure will increase greatly. A medical and technical equipment failure will not only cause expensive maintenance costs, but also lead to long service downtime, and the failure will affect nearly a hundred examination visits, which has a direct negative impact on the service capacity, work efficiency and patient satisfaction of MT department. Therefore, as a scarce medical resource, the uncertainty of the machine can also greatly affect the efficiency of medical examination services. In the capacity planning optimization problem of healthcare service, the uncertain failure of medical examination equipment is a factor that MT departments cannot neglect when controlling operating costs and improving patient satisfaction.

In recent years, the public demand for quality of medical services has been increasing, and in order to adequately allocate resources and patient triage, medical equipment capacity planning has begun to focus on the issue of priority of patients receiving medical services.

3. Overview of Healthcare Service Capacity Planning

In the field of healthcare services, capacity planning usually involves determining the service time and resources required for patients in advance. Therefore, the advantages and disadvantages of capacity planning have a great impact on the service quality and resource utilization of healthcare services. At present, healthcare service capacity planning has received increasing attention from scholars at home and abroad, and some of the research results have been applied in actual healthcare service scenarios. A summary of the existing literature on considerations, research service scenarios, research methods and typical representative literature is shown in Table 1.

Table 1: Essential Factors of Existing Research on Healthcare Service Capacity planning

Factors	Sectors	Methodology	Representative literature
Patient demand	Outpatient Clinic	Mathematical models (Markov decision making), Machine learning techniques (Time Series models, ANN)	[6],[9],[12]
Patient attendance behavior	Outpatient Clinic	Mathematical planning (Mixed integer planning, Dynamic planning), Machine learning, Robust models	[18]
Uncertain service time	Outpatient Clinic, Operating Theatre		[26],[23]
Healthcare service specificity	Medical Technology Department		[30],[32]

3.1. Overview of Healthcare Service Capacity Planning Considering Various Patient Demand

In general, the patient demand has been the focus of research in health care capacity planning. Many scholars believe that the extent to which the patient demand is met is a key factor in measuring the effectiveness of healthcare service capacity plans. Worthington et al. [5] used a projection method to evaluate capacity planning scenarios influenced by patient demand to determine the average waiting time for future demand scale medical and technical appointments. Bowers et al. [6] developed an integrated outpatient planning system that considered patient appointment times that integrates demand data into a single model of outpatient demand through data validation to ultimately determine the capacity of outpatients for diagnostics, tests, and treatments. Vermeulen et al [7] developed a dynamic method for determining a scheduling plan for CT scan appointment capacity in radiology based on patients' needs for different examination items. Demir et al. [8] considered the independent and dependent demand between different departments relationships and proposed a model to determine the required capacity for medical examinations by forecasting demand. Markov chain is one of the commonly used methods in the demand forecasting problem of medical services. Duan et al. [9] proposed a T-MCGM(1,1) model by combining Taylor approximation to gray Markov chain, and applied the model to forecast the demand of medical services for diabetes, heart disease and cerebrovascular disease in China from 2016 to 2022, finally found that there is a huge growth in the future demand of urban medical services. Xin Liu and Kai Gao [10] developed a gray GM(1,1) model to forecast the demand for healthcare facilities, physicians and admissions in healthcare services in China from 2020 to 2025 and found that the model fit well. Asamani et al. [11] estimated the future number of health facilities required in the health sector of Ghana based on Markov process prediction model, which was translated into health facility manpower requirements based on staffing criteria to inform the country's achievement of sustainable development goals.

With the gradual improvement of machine learning techniques, demand prediction models based on machine learning have been widely used in various service areas. Qiu et al. [12] compared the prediction effects of six machine learning algorithms (including LR regression, SVM, ANN, random forest, XGBoost, and optical gradient enhancer) to analyze the effects of different environmental factors such as air pollution and meteorological factors on medical demand, especially the impact of peak demand days for cardiovascular diseases. Barros et al. [13] used a neural network and support vector machine model to predict the demand for health services and managed the scarce resources based on the prediction results and found that the prediction model could be applied to various scenarios that capacity and demand are inconsistent so that managers could take corrective measures. Villani et al. [14] developed a time series trend model and used a seasonal auto-regressive moving average model to predict the attendance of diabetic emergency patients and found that the model had high accuracy in predicting MAPE values. Zhang et al. [15] used a hybrid ARIMA-SVR approach to predict daily radiology emergency department patient flow considering both linear and nonlinear patterns of emergency patient

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flow patient demand, and the results showed that the hybrid model outperformed the comparative model in terms of MAPE, RMSE and MAE values.

In addition, some scholars have used function derivations to estimate the quantity demanded in health care services, such as Davis and Fard [16] developed a flexible statistical model to approximate the probabilistic mass function of future hospital bed demand and derived the minimum mean absolute error of the ideal prediction to provide information for managers to optimize short-term staffing to accommodate bed demand. Yao et al. [17] projected the number of physicians demanded in China from 2020-2035 by constructing an unequal full combination model to provide a scientific reference for health human resource planning.

3.2. Overview of Healthcare Service Capacity Planning Considering Patient Attendance Behavior

In recent years, with the further improvement of the healthcare delivery system, the option and convenience of patient access has greatly increased and patients have more autonomy in the process of access, so patient reaching behavior will have a great impact on healthcare capacity planning. Hulshof et al. [18] developed an approximate dynamic planning framework in the context of an uncertain environment of patient treatment paths and arrival numbers, considering resource allocation and patient admission planning model with stochastic factors enables integrated decision making for hospital departments and resource networks. Aladeemy and Khasawneh [19] balanced nurse workload by inserting buffers into the plan and proposed a probability-based criterion to address service time uncertainty to develop an optimal appointment capacity plan for outpatient infusion centers. Nas and Koyuncu [20] developed a hybrid machine learning model to optimize optimal bed capacity in the emergency department by minimizing the required patient length of stay based on improving the accuracy of patient arrival time and loss rate prediction. Liu et al. [21] introduced a Markov decision process considering uncertain length of stay for postoperative patients, and the results validated the effectiveness of a capacity planning and allocation model based on downstream bed utilization. Samorani and LaGanga [22] predicted patients' no-show behavior based on individual appointment characteristics with appointment dates, and determined the optimal number of appointments with waiting time and overtime as targets under patient behavior uncertainty. Nguyen et al. [3] considered the uncertainty of random arrival of first-time patients versus repeat patients, and developed an on-time patient visit rate based on a guaranteed capacity planning model to determine the number of physicians needed for the outpatient system, emphasizing the importance of patient demand arrival uncertainty.

3.3. Overview of Healthcare Service Capacity Planning Considering Uncertain Service Time

There are various types of medical and health services, and the same medical services vary across physicians and patients' access scenarios. Symptoms of disease vary from patient to patient, and therefore service times vary tremendously. For different service scenarios extended in the diagnosis and treatment services, many scholars gradually included the service time uncertainty factors in the medical service environment into the research field and tried to build a medical service capacity delineation model in the uncertain environment. Peng et al. [23] proposed a two-stage robust optimization model to determine the optimal number of operating rooms and ICU beds based on uncertain operation time and postoperative ICU stay, with the help of ellipsoid and box uncertainty sets to portray uncertainty. Gokalp et al. [24] developed a capacity planning model for a stem cell donor network center, they approximated the maximum waiting time using a queuing theory approach and introduced a scenario-based stochastic planning approach to explore the impact of uncertain demand and service time on the capacity planning problem. Nasrabadi et al. [25], in their study of facility siting and capacity determination problems involving patients and healthcare facilities, considered service time and stochastic demand as short-term uncertainty and long-term uncertainty respectively, and found that the proposed queuing model performed better in improving service levels. Corlu et al. [26] considered service time and arrival uncertainty, with resource utilization and patient waiting time as optimization objectives, using Monte Carlo simulation and optimization models to determine the optimal number and location of buffer area servers.

4. Overview of Service Capacity Planning for MT Department

With the rapid development of modern medicine and science and technology, medical technologies such as imaging, MRI and ultrasound sensing have become important tools for healthcare and treatment services in medical institutions. Some special medical service departments, such as medical technology examination services in medical technology examination departments, have the special characteristics of "human-machine integrated" services, so the specificity in the service process of special departments has become an emerging research content for medical service capacity planning.

Carrasqueira [27] et al. focused on the development of photon therapy techniques in clinical practice and proposed an automated noncoplanar arc trajectory optimization framework designed in two modular phases that led to significant improvements in the quality of treatment planning for head and neck tumors. Mixed integer programming models have been widely applied to optimize treatment planning, staff allocation and resource scheduling problems in radiology departments. Cataldo et al. [28] developed two sub-problems to determine the effective capacity and intraday scheduling of chemotherapy sessions in cancer treatment centers, where the arrival of new patients, the latest start date specified for the session and the session interval were sources of uncertainty. Vermeulen et al. [29] developed a dynamic method for determining the capacity scheduling plan for radiology CT scan appointments in response to patients' demand for different examination items. Vieira et al [30] first generated demand levels based on historical patient data, then proposed a stochastic mixed-integer linear programming model to optimize the radiotherapy technician allocation problem. The objective function of this study was to maximize the number of patients who completed pre-treatment within a given waiting time. He [31] used a contraindicated search-based approach to solve the resource scheduling and allocation problem for radiology examination flow, where the authors improved the patient throughput in the radiology department by finding the optimal solution for resource scheduling and capacity allocation with the objective of minimizing the weighted sum of average examination flow time, average resource idle time and delay time as contingencies. Recently, several studies have focused on the uniqueness of technology-driven services in the medical technology sector and proposed various optimization strategies and models to improve the quality of radiology treatment planning. Inspired by the field of radiotherapy treatment planning (RTTP), Brooke et al. [32] formulated the fully discretized inverse planning as a split feasibility problem, studied the feasibility seeking problem with percentage violation constraints (PVCs), and described how their results can be applied to RTTP.

5. Conclusions

The results of the review indicate that outpatient appointments, inpatient beds and operating rooms are currently common research scenarios in the healthcare service capacity planning problem. Most scholars study how to allocate the capacity of resources such as human resources (e.g., number of physicians and working hours) and healthcare facility space (surgical blocks, inpatient beds) for healthcare services. When studying capacity planning for healthcare services, many scholars divide patient demand into appointment patient demand and on-site arrival patient demand based on whether appointments are made, or study patient demand in separate departments based on the requesting department in the appointment system. Among the factors of uncertain medical service environment that have emerged in recent years, patient's no-show behavior and uncertain service time are hot issues in domestic and international research. Diversity exists in modeling approaches, and models such as integer programming, dynamic programming, queuing theory, Markov decision making and stochastic programming are among the more common approaches in health care capacity planning studies.

Different healthcare service scenarios, service modes and resources involved in the service are all factors to be considered in the healthcare service capacity plan optimization problem. Because of the important impact of patient demand on healthcare service capacity planning, the independent and dependent relationship of multi-departmental patient demand should be considered based on the existing research on patient demand prediction. The disassembly of patient data for different patient flow data characteristics before targeting model construction are the future research trends for the healthcare service capacity planning patient demand level problem. For the healthcare service capacity planning problem considering patient arrival behavior, with the further increase in convenience and personalized service of patient access to care, a series of behaviors in the process of patient access such as first visit, follow-up visit and appointment change deserve in-depth research. For the study of medical service capacity planning considering service time, the main research scenarios currently lie in operating rooms and hospitalization, but due to the large number of medical resources involved in operating rooms and hospitalization, considering different resources to occupy service time becomes a possible research direction in the future. For the planning optimization of the number of inpatient beds, although the problem of bed deployment appears in a large amount of literature, how to develop appropriate bed deployment strategies based on hospital characteristics and the reasonable allocation of special high-consumption beds such as ICU is an important direction for future research on bed capacity planning.

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For medical service capacity planning considering service specificity, capacity planning of medical technology departments is the most common research scenario. Considering the specificity of service delivery through machines, the uncertainty of medical examination failures will be one of the important research directions. Since the satisfaction of patients with scheduled examinations varies according to the time of receiving medical and technical examination services, the problem of emergency scheduling or rescheduling of patients after the failure of medical equipment is also worthy of further study, among which the rescheduling strategy and the reasonable arrangement of the remaining equipment workload are difficult tasks. In addition, due to the wide range of patient sources in the medical technology departments, setting differentiated service priorities for patients is also important for capacity planning in special service units.

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