Article

Facilitating Patient-Centric Thinking in Hospital Facility Management: A Case of Pharmaceutical Inventory

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Abstract: Conventional hospital facility management (FM) focuses on reasonably allocating various resources to support core healthcare services from the perspectives of the FM department and hospital. However, since patients are the main service targets of hospitals, the patients' demographic and hospitalization information can be integrated to support the patient-centric facility management, aiming at a higher level of patient satisfaction with respect to the hospital environment and services. Taking the pharmaceutical services in hospital inpatient departments as the case, forecasting the pharmaceutical demands based on the admitted patients' information contributes to not only better logistics management and cost containment, but also to securing the medical requirements of individual patients. In patient-centric facility management, the pharmacy inventory is regarded as the combination of medical resources that are reserved and allocated to each admitted patient. Two forecasting models are trained to predict the inpatients' total medical requirement at the beginning of the hospitalization and rectify the patients' length of stay after early treatment. Specifically, once a patient is admitted to the hospital, certain amounts of medical resources are reserved, according to the inpatient's gender, age, diagnosis, and their preliminary expected days in the hospital. The allocated inventory is updated after the early treatment by rectifying the inpatient's estimated length of stay. The proposed procedure is validated using medical data from eighteen hospitals in a Chinese city. This study facilitates the integration of patient-related information with the conventional FM processes and demonstrates the potential improvement in patients' satisfaction with better hospital logistics and pharmaceutical services.

Keywords: patient-oriented; facility management; logistics management; pharmaceutical services; hospital environments

1. Introduction

The emergence of the COVID-19 pandemic has exerted tremendous pressure on the operation of hospitals and the delivery of satisfactory healthcare services and hospital environments to patients since early 2020. Leveraging state-of-the-art digital technologies, the digitalization of the healthcare sector sheds light on a promising pathway towards optimizing the use of medical resources and delivering high-quality healthcare services and hospital environments [1,2]. The healthcare services that are provided by hospitals are mainly delivered through two categories of processes: primary processes and infrastructure processes. The primary processes are those directly influencing the patients' state of health (e.g., performance of operations and intravenous injections), while the infrastructure processes are relevant for the provision of necessary resources (e.g., personnel, drugs and medicines) and deliver the functionality of primary processes through maintenance and other activities, such as the development, maintenance, security and operations of

healthcare facilities [3]. Extensive studies have been conducted to assess the quality of healthcare services that are directly delivered through primary processes in hospitals, mostly according to the patients' perceptions [4]. However, it is still an open question how to raise the effectiveness of healthcare service delivery through better hospital facility management work processes [5]. Intending to integrate and align the non-core services that are required to operate and maintain a business to fully support the core healthcare services, the hospital facility management oversees a series of infrastructure processes, ensuring the 24-h operation of the hospital to meet patients' needs, including but not limited to keeping tabs on the inventory and demand of medical equipment and supplies. Although the patient-centric service atmosphere in hospitals is greatly advocated, the current research on hospital FM still focuses on efficiency generation and cost savings from the FM departmental and organizational perspective. This leads to better performance with regards to the hospital, but not necessarily for the patients. Patient-centric facility management is becoming an interesting topic for hospitals and relevant stakeholders to provide more generalized FM services and better hospital environments, which effectively identify service gaps and satisfy patients.

Logistics management in hospitals is a complex process that deals with various material requirements, including pharmacy items (e.g., drugs, medicines, medical devices) and non-pharmacy items (e.g., office equipment, foods, linens). The procurement, distribution, and inventory of these resources through more flexible supply chains contribute to better pharmaceutical management and inventory management in hospitals, which are fundamental elements to hospital facility management. Particularly, for supporting pharmaceutical services of hospitals, optimal inventory control strategies can proactively minimize the risks of excess stock and stockouts [6]. In this case, most attention has been given to uncertainties and variability in the supply chain, economic constraints, the availability of human resources to place orders, receive deliveries, and store goods, which stands from the point of view of the FM department in hospitals [7]. On the other hand, this paper discusses the necessity of bringing patient information into the logistics/inventory management and facilitating better facility management and corresponding supply chains from patients' perspective, treating the pharmacy inventory as the aggregated medical resources reserved for individual patients. The patient-centric facility management perspective helps to further reduce the inventory level and total inventory cost of pharmacy items by modelling the relationships between the demand of pharmacy items in a hospital, and the diagnosis, estimated length of stay and other patient information.

The rest of this paper is organized as follows. Section 2 reviews patient-centric facility management, logistics management, and a pharmaceutical service based on patient-centric thinking. Section 3 presents a patient-centric pharmaceutical service and the two accompanying forecasting models. Section 4 uses a case study to demonstrate the patient-oriented pharmaceutical management leveraging the demographic and hospitalization information of admitted patients, while Section 5 concludes the paper.

2. Literature Review

2.1. Patient-Centric Facility Management in Healthcare Environment

The exploration of how FM can be improved and differentiated in a healthcare environment is not new in the academic field [8–13]. However, it was not until recently that researchers have paid attention to investigating how patients and their demographic data can be utilized to provide a patient-centric FM [14]. Patient-centric facility management in this paper is defined as "the integration of processes within a healthcare organization to deliver and maintain required services which support efficient and timely medical care activities to meet patients' needs." This is a synthetic definition that combines the Normalization definition of FM [15] ("the integration of processes within an organization to maintain and develop the agreed services which support and improve the effectiveness of its primary activities") and Yavorskyi's [16] patients-centric criteria for the healthcare sector ("include effective and timely medical care, efficient use of the resources, meeting

the patients' needs and treatment efficiency"). In other words, patient-centric FM aims to meet the patients' needs by providing healthcare FM service support without interrupting the medical emergency, surgical, specialized chronic care, and rehabilitation services. It is worth noticing that healthcare FM services frequently share quite different characteristics from the other commonly encountered FM environments (e.g., residential buildings, general-purpose offices, etc.) in the following two ways. Firstly, the main content of the hospital FM service is different from other general building types of FM services. For instance, the operation cost of "sterile goods supply" and "maintenance of medical equipment" could take up 42 per cent and 14 per cent of a typical hospital project, which will not be found in an office building's FM service expenditure [3]. Secondly, the service standard of healthcare FM is higher than the other general types of building FM services. Taking sterile goods supply as an example, once a surgical kit is opened, no matter its size, the untouched content needs to be sterilized and repacked in any case. The cost of supplying sterile goods is dominated by content (i.e., the surgical operation type) and the quantity, rather than the length of the procedure [3].

Several important characteristics of FM in the hospital environment are highlighted above. These characteristics make patient-centric FM vital for the digital-era hospital environment. Although the majority of hospital FM consumables are manufactured physical goods that are produced and consumed at different times, some healthcare FM services (e.g., catering services) are delivered and consumed simultaneously [17]. Therefore, it is essential to collect and analyse the patients' entry and hospitalization information to predict the busy and off seasons more accurately, in order to ensure that the stocks are sufficient for both medical and non-medical consumables. Next, it is also crucial for integrating the patient's demographic or personal properties into the service delivery process. For example, the nutrition, medical consumables, ventilation and indoor air quality requirements for patients with different types and stages of diseases vary significantly. Accurate forecasting of the patients' demand for different medical and non-medical consumables is vital in predicting the aggregate FM service demand within a specified time. Lastly, patients are always the main service objects for healthcare facility management in hospitals. Again, taking the hospital's catering service as an example, some patients are likely to require a special meal due to the specific diet style or allergy, making the service more customized to patients' needs rather than just providing a standardized FM product. It is suggested that patients' diverse perspectives should be valued in designing FM processes [17].

With the patient-centric FM thinking involved, bottleneck problems can be better tackled in the facilities management process of hospitals. Firstly, during healthcare-service delivery, long waiting times are often treated as a symbol of low service quality [18]. Patients are still suffering long waiting times, "bed-blockers", and under-maintained facilities (e.g., the unplanned maintenance of operating theatres), which negatively impact their quality of life due to their potentially worsening condition when waiting to receive treatment. Unplanned maintenance and equipment malfunction are two of the main causes of such issues. It is suggested that the facility manager lacks the patients' demographic information, such as length of stay, which stops the FM manager from further predicting the hospital facilities' utilization level to make a better facility maintenance plan that minimizes the disruption of the hospital's specialized medical activities. The second aspect of improvement is communication. It is suggested that the communication with the hospital supply chain partners could also be further improved with more frequent contact [19,20]. Digital logistics management should be designed to integrate patients' information in a timely manner, allowing for more agile hospital logistics management. The lack of information integration is a major obstacle for patient-centric FM in a digital logistics management environment. In the current hospital information management framework, there is only very limited patient-centric information communication between the major medical department and the FM department. However, without the information integration between the different departments, the department-wise decision is frequently more focused on the short-term benefits of their own department, rather than the long-

term benefits of the entire organization/hospital [21]. In summary, the new digitized hospital logistics management environment should integrate FM information flow with patient-related information flow inside the hospital (e.g., pharmaceutical information flow).

2.2. Logistics Management and Pharmaceutical Service

With the increase in public health emergencies and the ageing population, the surge in healthcare demand poses severe challenges to the capabilities of healthcare infrastructure [22,23]. The management capability to suddenly increase inpatients has a significant impact on the healthcare facility resilience, such as the bed-occupancy levels and the stability of flows into the hospitals. One of the main factors for FM is the patients' admission time. For example, prioritizing and differentiating the admission time of patients with different symptom levels can greatly relieve the capacity and management pressure of healthcare facilities and FM during the COVID-19 period. Furthermore, to provide satisfactory health services and hospital environments, optimizing healthcare resource supply and allocation is one of the most significant global issues in terms of sustainability and equity [24]. Healthcare logistics stands for an integrated approach to healthcare supply-chain design, holding the potential to deal with the emerging demand shortage and efficiency improvement needs from the hospital FM perspectives [25]. In hospitals, logistics management consists of conventional physical flows, associated information flows and other emerging flows, such as patients, throughout the care chain [26]. Supply chain management is the backbone of these healthcare deliveries. The practice of the healthcare supply chain is defined as "a set of activities undertaken in an organization that helps the organization in the effective management of its supply chain by integrating its stakeholders such as manufacturers, distributors, suppliers and customers" [27]. By supporting the supply chain with more focus on patients, especially the admission time of patients, the healthcare logistics management can flexibly adjust the stock and promote the efficiency of the hospital pharmacy and FM. Although various healthcare tasks (e.g., diagnosis, treatment, and management) put pressure on logistics, they also generate a large scale of daily datasets [12,28]. Capturing added value from these datasets is expected to benefit the hospital information flows and further improve the healthcare supply chain and operational efficiency [26]. Besides, the adoption of digital technologies and methods can transform how patients receive healthcare services by utilizing these datasets for logistics improvement schemes. In practice, healthcare organizations are trying to acquire these advanced capabilities to improve logistics management in terms of finance, administration and medicine.

Existing studies have widely explored potential solutions to advance these capabilities. However, few of them focus on patient-centric solutions. Further, various challenges arise from (1) logistic issues; (2) digitalization issues. For healthcare logistics, the main challenges that are identified in the literature include overstocking [29], inventory shrinkage [30], fragmented processes [31], delivery delay [32] and unpredictability [33]. These challenges reflect that many processes are still paper-based labour-intensive activities in healthcare logistics and lack standardization, visibility, and traceability. Conventional approaches to healthcare logistics prevent the capture of advanced capabilities. The main hurdles to digital transformation in healthcare services involve technological factors, such as information flow integration/sharing, data capturing that is associated with patients and personal health, algorithms, performance-measurement tools, and nontechnological barriers, such as cultural resistance, organizational structure and governance [34]. These phenomena reflect that the introduction of digital technology is still a rhetoric-based initiative. Further, there is still long way to go for the industry to fully embrace digitalization, which is not a last mile problem. With the progress of digitalization, if these obstacles are not resolved appropriately, they may fail the transformation, and the operational efficiency may be even worse than conventional logistic methods.

The aim of pharmaceutical logistics is "placing the right drugs and medical supplies, in the right quantities, in the right conditions, at the right health service delivery points, at the right time, for the right patients/users and for the right cost" [35]. There is a four-step pro-

cess from the acquisition in the market to the distribution to wards: (1) drug reception and warehouse/pharmacy operations; (2) request and validation; (3) transportation; (4) ward drug management [36]. However, there are existing conventional logistics management problems. For example, improper hospital drug inventories may cause shortages or stagnant supplies. Besides, traditional logistics basically occurs without the assistance of digital technologies. Subsequently, many studies notice that introducing information and communication technology will be an essential strategy to improve patient safety and reduce drug consumption. Some techniques have been introduced into logistics management to facilitate the efficiency improvement of pharmaceutical services, including geographic information systems [37], beacon technology [38], unmanned aerial vehicles [39], blockchain [40] and so on. A series of advanced digital approaches are necessary to develop enhanced analytical capabilities for the existing conventional logistics management problems that are mentioned above, one of which is to accurately forecast the pharmaceutical demands for optimizing the supplies and inventory of drugs, medicines, and medical devices.

Some studies have applied advanced computing techniques to forecast, plan or monitor the pharmaceutical supply chain. Qin et al. [35] introduced cluster computing to monitor and manage drug logistics. Ershadi and Ershadi [41] proposed a multi-objective optimization model to plan the pharmaceutical supply chain. Du et al. [42] combined the genetic algorithm with a BP neural network for drug inventory management. Nikzad et al. [43] proposed a two-stage stochastic programming approach for drug inventory routing problems. Saedi et al. [6] developed a stochastic optimization framework to find the optimal drug stock levels and order quantity levels. However, existing studies ignore the fact that hospital service aims to serve patients [44–47]. The patient-centric FM perspective is vital in this sense, and it is expected to improve hospital pharmacy inventory-management efficiency, especially for the inpatient departments in hospitals. Thus, there is a research gap to develop a patient-centric demand-forecast procedure for estimating the total amount of pharmaceutical services and products that are needed by integrating digital methods, logistics management and patient-centric FM thinking.

3. Patient-Centric Pharmaceutical Services

To respond to the clinical requests coming from different departments (e.g., inpatients, outpatients, operating rooms, etc.), the stocks of drugs and medicines need to be controlled cautiously to satisfy various demands from patients. Moreover, considering the high purchase and stocking costs of many drugs and medicines (e.g., the need to be kept in refrigerated storage rooms) and the shortage of staff working in pharmacies, the pharmacy inventory must match the corresponding demands to avoid the expiration and unnecessary immobilization of medical resources [48]. In this study, to optimize the drug and medicine supplies and consequently improve the pharmaceutical services that are delivered to patients for the inpatient departments in hospitals, a demand forecasting procedure integrated with patient-centric FM thinking is proposed to reduce the risk of excess stock and drug shortage, which endanger hospital profitability and the patient experience.

Instead of focusing on the historical demand data and using time series forecasting models (e.g., moving average, exponential smoothing) to recognize data patterns, this study uniquely proposes a patient-centric demand forecast procedure to guide the adjustment of supplies and inventories, and further guarantee the pharmaceutical services. In this procedure, the inventory in the hospital inpatient department is regarded as the combination of the drugs or medicines that are allocated to every single patient. The drugs and medicines are explicitly claimed by specific patients until being released after they are discharged from the hospital. It is assumed that the supporting supply chain ensures the pharmacy inventory always satisfies the need of all these patients without surplus stock. To achieve this goal, this study developed two forecasting models based on the Support Vector Regression (SVR) under two study scenarios, as shown in Table 1. The first forecasting model uses input variables of inpatient demographic and initial hospitalization information, including expected days in the hospital, gender, age, and diagnosis type, to

predict the inpatients' total medicine consumption during the hospitalization. The second forecasting model predicts the amended and updated patient's length of stay using all demographics, hospitalization, and the patient's early-stage medical consumable information (i.e., resuscitation medicine and surgical related consumables). The SVR model is adopted due to its suitability for small sample-size learning. The mathematical form of the nonlinear SVR is given as follows, in which the *K* is the Gaussian Radial Basis function.

$$f(u) = \beta_0 + \sum_{i=1}^{n} \alpha_i K(x_i, u)$$

$$K(x_i, u) = e^{-\frac{|x_i - u|^2}{2\sigma^2}}$$

Table 1. Two forecasting models for estimating patient medical consumption.

Study Scenario	Input Variables	Output Variables
Early consumption allocation	Patient (estimated) days in hospital	Medicine consumption (counts)
	Patient gender	Medicine consumption (quantity)
	Patient age	Medicine consumption (cost)
	Patient disease type	-
Updated length of stay and allocation	Patient resuscitation medicine and surgical related consumables (counts)	Updated patient length of stay
	Patient resuscitation medicine and surgical related consumables (quantity)	-
	Patient resuscitation medicine and surgical related consumables (cost)	-
	Patient gender	-
	Patient age	-
	Patient disease type	-

Figure 1 explains the detailed implementation of the demand forecasting procedure that is integrated with patients' information using these two forecasting models. Once a patient is admitted to the hospital inpatient department, the first forecasting model is adopted to preserve the drugs and other medical resources, according to the gender, age, disease type, and the initial estimated days of hospitalization. Preserved drugs and medical resources (early allocation) are claimed and allocated to the use of the specific patient only. After the early treatment, the second forecasting model is utilized to rectify the patient's estimated length of stay and update the allocated drugs and medical resources (updated allocation) based on the resuscitation medicine or surgical related consumables that are used during the early treatment. The remaining drugs and medicines are released to the inventory as unused resources once the patient is discharged from the hospital. Using this procedure, the pharmacy inventory becomes patient-centric, and the drugs and medicines that are used by specific patients are claimed and rectified based on the inpatient's demographic and pathogenetic condition. With the help of the supporting supply chain, the hospital pharmacy can run more efficiently by flexibly adjusting the stock, according to the demands of all admitted patients.
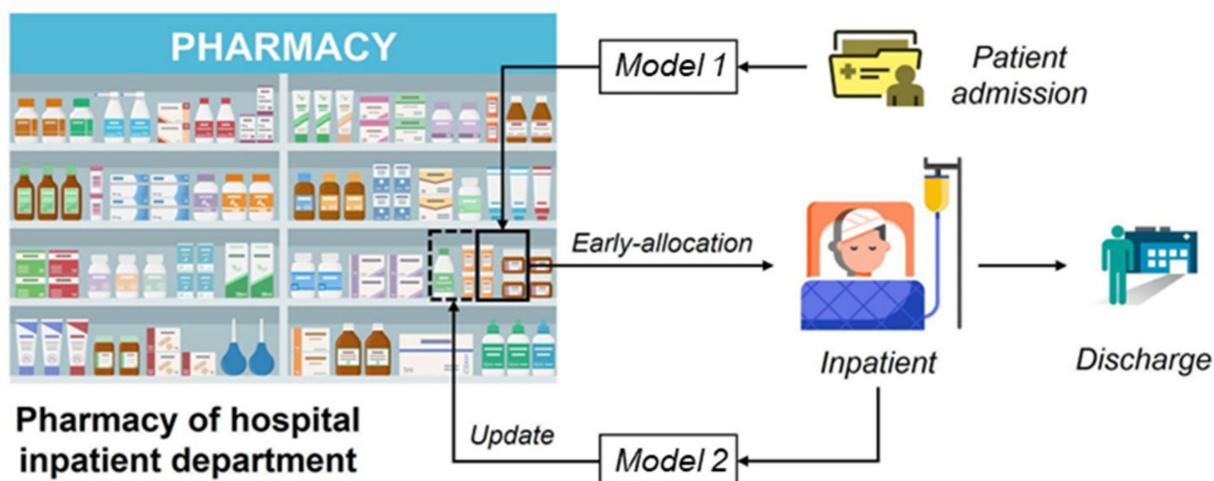
Figure 1. Patient-centric drug and medicine demand forecasting procedure.

Alongside the forecasting models for these two study scenarios, a correlation analysis is conducted to reveal the dependencies between the use of different drugs and medical resources. The goal of this correlation analysis is to identify the groups of medical consumable "packages" that are used by patients in bundles. This can help the hospital's pharmacy department to control the drugs and medical supplies with better logistics management.

Moreover, the proposed procedure is particularly useful in the face of the COVID-19 pandemic. On the one hand, this is an emerging infectious disease that lacks sufficient historical data for directly estimating the hospital-level demand. By estimating the individual demands and aggregating the individuals into the overall hospital demand, it is more feasible to make best use of the patient data, since significant divergences exist between patients due to demographic characteristics [2]. On the other hand, during COVID-19, the days of inventory and stock turns become much shorter due to the high demand. Estimating the patient-level demand potentially leads to a faster response to patients' needs [49].

4. Case Study

4.1. Research Data

The two forecasting models that were trained within this study utilized the data from inpatients who were admitted to eighteen different hospitals in a southeast coast city of China. The data range from 14 April 2019 to 30 April 2021, with the diagnosis of myocardial infarction (MI) and tuberculosis (TB), referred to as I21 and A15 in the International Classification of Diseases, Tenth Revision (ICD-10) Codes. The reimbursement records of 1571 inpatients have been extracted from hospitals' electronic health records system (including the demographic information, hospitalization information, and consumable count, quantity, and consumption information). Except for variables with the consumable count, quantity, and consumption information, all the other variables are independent and contain the patient's activities during the hospitalization. The demographic information, hospitalization information variables, and a sample of the consumable count (the number of charges), quantity (the number of consumables), and consumption (indicates the monetary cost of the consumables) information are summarized in Table 2.

Table 2. Study's raw data.

Category	Number of Variables	Specific Variables
Demographic information	3	Inpatient number, age, gender
Hospitalisation information	13	Personnel number, days in hospital, hospital code, name of primary diagnosis, master diagnostic code, project/consumable number, project/consumable name, project/consumable specification, unit of project/consumable, project/consumable unit price, project/consumable quantity, total bill cost, bill number
Consumable count, quantity, and consumption information	4018	Aspirin, clopidogrel hydrogen sulfate, Tegretol, atorvastatin, rosuvastatin, metoprolol succinate, captopril, enalapril, benazepril, nitroglycerin, coronary balloon dilation catheter, coronary stents, diagnostic guidewire, intravascular angiography catheters, etc.

4.2. Data Pre-Processing

The dataset that is used for this experiment only contains the myocardial infarction inpatient information. Table 3 shows the characteristics of the mentioned variables with their corresponding proportion or mean (standard deviation). These variables are classified into demographic, hospitalisation, and consumable quality & cost information. The major characteristics of this study's cohort were male (78.49%) with the patients' mean age at 63.13. From the entire dataset, 90% was used as the training set for tuning and training the model, while the remaining 10% was used as the test dataset.

Table 3. Variables of the dataset.

Factors	Proportion or Mean
Demographic information	
Sex, male (%)	78.49
Age [mean (SD)]	63.13 (15.92)
Hospitalisation information	
Days in hospital	
Less than 10 days (including upper boundary) (%)	68.36
Between 10 and 20 days (including upper boundary) (%)	25.97
Between 20 and 30 days (including upper boundary) (%)	3.69
Above 30 days (excluding lower boundary) (%)	1.97
Average days in hospital (before 2020/04/15) [mean (SD)]	9.35 (7.51)
Average days in hospital (after 2020/04/15) [mean (SD)]	9.97 (7.78)
Total number of project/consumables per patient (under unique inpatient number)	1580.91 (3200.27)
Average number of project/consumables per patient per day (under unique inpatient number)	158.1 (180.39)
Total cost of project/consumable per patient (under unique inpatient number)	51,449.69 (45,193.50)
Average cost of project/consumable per patient per day (under unique inpatient number)	6620.46 (7313.68)
Consumable quantity & cost information (selected)	
Average count of aspirin per patient [mean (SD)]	1.237 (2.163)
Average quantity of aspirin per patient [mean (SD)]	19.249 (13.858)
Average count of atorvastatin per patient [mean (SD)]	0.950 (1.870)
Average quantity of atorvastatin per patient [mean (SD)]	11.167 (13.348)
Average count of metoprolol succinate per patient [mean (SD)]	0.752 (1.900)
Average quantity of metoprolol succinate per patient [mean (SD)]	7.947 (11.432)
Average count of captopril per patient [mean (SD)]	0.012 (0.115)
Average quantity of captopril per patient [mean (SD)]	0.037 (0.489)
Average count of nitroglycerin per patient [mean (SD)]	0.934 (0.625)
Average quantity of nitroglycerin per patient [mean (SD)]	5.233 (14.183)
Average count of coronary balloon dilation catheter per patient [mean (SD)]	0.326 (0.764)
Average quantity of coronary balloon dilation catheter per patient [mean (SD)]	0.344 (0.834)
Average count of diagnostic guidewire per patient [mean (SD)]	0.404 (0.566)
Average quantity of diagnostic guidewire per patient [mean (SD)]	0.491 (0.733)

Before the primary screening, variables that had insufficient information entries (e.g., the consumables that were consumed by less than 20 different inpatients) were un-

picked. In the end, there are 21 variables left that will be used as the input for the forecasting model. After the primary screening of the acquired data, it is suggested that variable inconsistency issues and unclassified activity issues need to be resolved for the collected raw dataset. Therefore, three pre-processing activities have been carried out to make the raw data ready for the model training. First, the consumable specifications and names for the same type of medicine are not consistent. For instance, both "Nitroglycerin" and "Nitroglycerin injection" have been used for the name of the same item. Therefore, the first step of the data preparation process is to standardize the name of medicine or other medical consumables with common main ingredients to use the same name. Second, it is found that the medical activities, medicines, and other medical consumables share the same variable category, which hinders the dataset's capability to conduct more advanced data analysis. As a result, works have been carried out to separate all the data entries into three groups: medical activities, medicines, and other medical consumables. Finally, works have also been carried out to eliminate the rarely occurred activities/consumables/medicines intake.

4.3. Pharmaceutical Demand Forecasting Results

Using patient-oriented thinking, three main findings can be summarized from the regression result of the early consumption allocation study (the first scenario in Table 3).

- The regression models' results for medicines' counts and quantity output are optimistic, with a satisfied root mean squared error (RMSE) and mean absolute error (MAE);
- The regression results vary significantly across the different drug categories. The multi-output regression result for angiotensin-converting enzyme inhibitors (including captopril, enalapril, benazepril, and ramipril) used for myocardial infarction have the lowest RMSE and MAE (Table 4). This is partially due to the infrequent use of the angiotensin-converting medicines, which is supported by their relative low R squared scores;
- The performance of the different medicines is more consistent for the "Counts" and "Quantity" output rather than the "Cost" output. For instance, aspirin has a higher mean square error (at 201.575) than that of clopidogrel hydrogen sulfate (at 110.349) when using the quantity output. However, the mean squared error of aspirin (at 47.561) is much lower than that of clopidogrel hydrogen sulfate (at 4944.783) when using the cost as the output variable unit. There are several reasons behind this: (1) the difference in the unit price of the different manufacturers; (2) the difference in the composition produced by the different manufacturers; (3) the potential price difference due to the drug dosage forms. The result suggests that: (1) the general result for the medicine demand forecast is satisfied; (2) the regression forecast errors for angiotensin-converting enzyme inhibitors are significantly lower than the rest of the medicine groups; (3) the forecast for a better medicine quantity intake forecast might not necessarily lead to a better medicine cost forecast.

Regarding the regression result for the updated length of stay and allocation study (the second scenario in Table 3), the updated patient length of stay does not vary significantly when using different input medical and surgical-related consumable variables (count, quantity or cost). As shown in Table 5, it gives similar RMSE and MAE for the patient's expected and updated days in the hospital, which indicates that the resuscitation medication and surgical-related consumable variables can accurately reflect the severity level of patients and give informative clues to their estimated length of stay.

Table 4. Early consumption allocation scenario: multi-output regression forecast results for 10 typical medicines.

Measure	Aspirin	Clopidogrel Hydrogen Sulfate	Tegretol	Atorvastatin Calcium	Rosuvastatin	Metoprolol Succinate	Captopril	Enalapril	Benazepril	Ramipril
Root mean squared error (counts)	2.960	1.517	2.555	2.781	1.251	2.584	0.218	0.200	0.525	0.250
Mean absolute error (counts)	0.851	0.528	0.830	0.941	0.457	0.940	0.208	0.200	0.258	0.223
Root mean squared error (quantity)	14.198	10.505	21.973	12.136	9.038	11.368	0.253	0.200	2.839	2.749
Mean absolute error (quantity)	10.318	4.175	16.977	9.069	3.989	6.710	0.214	0.200	0.636	0.685
Root mean squared error (cost)	6.896	70.319	194.506	63.510	41.369	24.343	0.180	0.200	7.802	9.781
Mean absolute error (cost)	4.944	25.121	145.998	39.581	14.180	14.366	0.180	0.200	1.522	1.798

Table 5. Updated length of stay scenario: regression forecast results for length of stay.

Measures	Days in Hospital
Root mean squared error (counts)	6.628
Mean absolute error (counts)	4.220
Root mean squared error (quantity)	6.561
Mean absolute error (quantity)	4.107
Root mean squared error (cost)	6.688
Mean absolute error (cost)	4.102

Overall, through the comparison of the different test input and output data variable (Quantity) profiles, some medical consumables, such as nitroglycerin, seem to provide more slightly better support for the forecast of the patients' expected days that will be spent in hospital.

4.4. Correlation Analysis Results

Various medicines are used during the treatment of myocardial infarction. In many cases, some medicines are used complementarily or as the substitute to other medicines with similar effects. The correlation analysis is conducted to calculate the correlation coefficient values between different medicines inside a single medication group or across the group portfolio and reveal the complement and substitute relationship of the different medicines. The selected groups of consumables are: (1) drugs for the prevention of thrombosis (in coral blue); (2) drugs for the lowering of cholesterol (in deep peach); (3) receptor clocker drugs (first scenario in Tables 6 and 7); (4) resuscitation drugs (in silver chalice); (5) coronary intervention equipment (in sea mist); angiography equipment (in salad green) (second scenario in Tables 8 and 9). According to Tables 6 and 7, the average correlation coefficient for using the counts of appearance output is obviously higher than the average correlation coefficient using quantities as the output variable, which might be related to the prescribing habit of specialist doctors, the standard treatment process, and patients' different conditions. Although the correlation values are quite different when using counts and quantities for analysis, consistent conclusions can be made based on the correlation analysis results. For instance, the correlation coefficient of clopidogrel hydrogen sulfate and Tegretol is negative (at -0.084 (counts) and -0.356 (quantity)), which indicates that these two medicines are substitute for each other. While still inside the same anti-thrombotic drugs group, the correlation coefficient values of the aspirin against both clopidogrel hydrogen sulfate and Tegretol are positive, revealing the relationship between these two connections to be complementary. It is also suggested that a higher correlation coefficient value in the concurrent appearance count will not necessarily lead to a higher correlation coefficient value in the quantity of medicine used. For instance, the correlation coefficient of atorvastatin calcium and metoprolol succinate score the highest at 0.781 using the count of appearance, while their correlation coefficient only reaches 0.21 when the quantity variables are calculated. For facilitating better pharmaceutical services, correlation relationships on quantities rather than counts can be used to guide the pharmaceutical inventory, considering the complement and substitute relationship between medicines. Therefore, it is suggested that using the quantity variable might be able to identify and determine some hidden but highly valuable relationships between the different medicines for configuring the pharmaceutical inventories. For instance, in Table 9, the correlation coefficients between nitroglycerin and other consumables are very small or even negative in terms of the quantity, while in Table 8, the correlation coefficients are much larger in terms of count. The found relationships can guide the pharmaceutical inventory, which is further discussed in the next section.

Table 6. The comparison of the correlation analysis results for medicines used for Scenario One's study using counts variable.

	Aspirin	Clopidogrel hydrogen sulfate	Tegretol	Atorvastatin calcium	Rosuvastatin	Metoprolol succinate
Aspirin	1.000					
Clopidogrel hydrogen sulfate	0.696	1.000				
Tegretol	0.547	−0.084	1.000			
Atorvastatin calcium	0.652	0.534	0.417	1.000		
Rosuvastatin	0.387	0.305	0.231	−0.113	1.000	
Metoprolol succinate	0.765	0.611	0.510	0.781	0.230	1.000
Mean (per inpatient number by column)	1.237	0.561	0.820	0.950	0.327	0.752
Standard deviation (per inpatient number by column)	2.163	2.019	1.417	1.870	1.135	1.900

Average correlation
0.431

The ratio of average quantity of consumable between four selected consumables (scaled based on the smallest average consumable)
3.79:1.72:2.51:2.91:1:2.30

Table 7. The comparison of the correlation analysis results for medicines used for Scenario One's study using quantity variable.

	Aspirin	Clopidogrel hydrogen sulfate	Tegretol	Atorvastatin calcium	Rosuvastatin	Metoprolol succinate
Aspirin	1.000					
Clopidogrel hydrogen sulfate	0.198	1.000				
Tegretol	0.557	−0.356	1.000			
Atorvastatin calcium	0.279	0.220	0.139	1.000		
Rosuvastatin	0.275	0.014	0.350	−0.355	1.000	

Table 7. *Cont.*

	Aspirin	Clopidogrel hydrogen sulfate	Tegretol	Atorvastatin calcium	Rosuvastatin	Metoprolol succinate
Metoprolol succinate	0.377	0.232	0.256	0.210	0.124	1.000
Mean (per inpatient number by column)	19.249	6.188	20.012	11.167	5.162	7.947
Standard deviation (per inpatient number by column)	13.858	13.721	21.742	13.348	10.932	11.432
Average correlation 0.168						
The ratio of average quantity of consumable between four selected consumables (scaled based on the smallest average consumable) 3.73:1.20:3.88:2.16:1:1.54						

Table 8. The comparison of the correlation analysis results for resuscitation medicine and surgical related consumables used for Scenario Two's study using counts variable.

	Nitroglycerin	Coronary balloon dilation catheter	Coronary stents	PTCA dilatation catheters	Diagnostic guidewire	Intravascular angiography catheters	Contrast syringe
Nitroglycerin	1.000						
Coronary balloon dilation catheter	0.145	1.000					
Coronary stents	0.326	0.397	1.000				
PTCA dilatation catheters	0.289	0.003	0.576	1.000			
Diagnostic guidewire	0.295	0.528	0.327	0.174	1.000		
Intravascular angiography catheters	0.385	0.309	0.373	0.336	0.528	1.000	
Contrast syringe	0.252	0.495	0.313	0.135	0.640	0.485	1.000
Mean (per inpatient number by column)	0.934	0.326	0.822	0.773	0.404	0.500	0.291
Standard deviation (per inpatient number by column)	0.625	0.764	0.935	1.025	0.566	0.506	0.460
Average correlation 0.348							
The ratio of average quantity of consumable between four selected consumables (scaled based on the smallest average consumable) 3.21:1.12:2.83:2.66:1.39:1.72:1							

Table 9. The comparison of the correlation analysis results for resuscitation medicine and surgical related consumables used for Scenario Two's study using quantity variable.

	Nitroglycerin	Coronary balloon dilation catheter	Coronary stents	PTCA dilatation catheters	Diagnostic guidewire	Intravascular angiography catheters	Contrast syringe
Nitroglycerin	1.000						
Coronary balloon dilation catheter	−0.055	1.000					
Coronary stents	0.023	0.332	1.000				
PTCA dilatation catheters	0.046	0.032	0.621	1.000			
Diagnostic guidewire	−0.024	0.508	0.281	0.180	1.000		
Intravascular angiography catheters	−0.029	0.289	0.334	0.301	0.479	1.000	
Contrast syringe	−0.004	0.469	0.258	0.134	0.642	0.453	1.000
Mean (per inpatient number by column)	5.233	0.344	0.977	0.919	0.491	0.521	0.351
Standard deviation (per inpatient number by column)	14.183	0.834	1.147	1.288	0.733	0.546	0.600
Average correlation 0.251							
The ratio of average quantity of consumable between four selected consumables (scaled based on the smallest average consumable) 14.92:0.98:2.79:2.62:1.40:1.48:1							

4.5. Improving the Hospital FM and Hospital Environments with Patient-Centric Data Analysis

In this section, the focus is on discussing how the pharmaceutical forecasting results and correlation analysis results can be used to benefit the FM (e.g., pharmaceutical logistic management) and its efficiency in providing better services and hospital environments to patients.

4.5.1. Benefits of the Healthcare Logistic Management with Pharmaceutical Forecast and Correlation Analysis

Given the results of the pharmaceutical demand forecast and correlation analysis in Sections 4.3 and 4.4, the forecast and correlation coefficient of the target groups of consumables and the ratios of averaged consumable quantity can be obtained after analysing the inpatient demographic and hospitalization data. It is implied that the typical ratio of consumables' average quantity can be used as the checking criteria for the "consumables bundles". According to the absolute correlation coefficient values, some pairs of consumables with a coefficient larger than 0.5 (indicating significantly correlated), such as diagnostic guidewire and contrast syringe, can be treated as the "consumable bundle". Taking diagnostic guidewire and contrast syringe as an example, the correlation coefficient of these two consumables is 0.642 (highly correlated), which means they can be treated as a package. Therefore, their ratio of average quantity (1.40:1) can be used as the benchmark to set the automated stock alarm system for the storage of consumables. When the diagnostic guidewire demand for a specific period is high (given by the early-consumption allocation prediction), the low stock rate of diagnostic guidewire will not only trigger the procurement reminder for diagnostic guidewire, but also check and remind (if necessary) the stock and procurement process of contrast syringe, according to their ratio of average quantity.

It is also implied that this consumable stock's auto-checking mechanism can remind the restock of potentially underlying correlated items belonging to a different medical consumable categorization group. For instance, the diagnostic guidewire and coronary balloon dilation catheter belong to angiography and coronary intervention-related consumables, which is different from diagnostic guidewire and contrast syringe that both belong to the same category (angiography). Using inpatients' demographic and hospitalization data, these hidden or implicit correlations can be revealed and considered by facility managers.

4.5.2. Benefits of the Estimated Patient Length of Stay

In addition to promoting better pharmaceutical services and hospital environments to inpatients, the demographic and hospitalization information of these patients can also help the facility managers better plan facilities' preventive maintenance and workspace management. Given the prediction results of patients' length of stay, facility managers will be able to anticipate the busyness level of the hospital in general and the busyness level of corresponding facilities serving specific inpatient groups with specified disease types. This is because the use of many hospital facilities is mostly disease oriented. The number of patients for a specific group of diseases will determine the utilization level of these facilities. As a result, given the analysis result of patients' demographic and hospitalization data, facility managers are provided with more supportive information to make the operation and maintenance decision with a better order of priority. For example, more accurate forecasting of the inpatients' length of stay helps to determine the capacity of the hospital to admit new patients and contributes to improving the turnover rate of hospital beds and other facilities.

5. Conclusions

With the rapidly increasing healthcare demand and seriously constrained medical resources, more attention has been focused on optimizing the usage of medical resources and the delivery of high-quality healthcare services and hospital environments. The non-core facility management in the healthcare environment, which is critical to supporting and improving the effectiveness of the primary medical care activities, are highlighted in this

paper. The definition of patient-centric facility management is explored, and the challenges and opportunities of using patient-centric FM thinking in hospital logistics management are discussed. Specifically, to facilitate better pharmaceutical services, the pharmacy inventory is considered as the aggregated medical resources (e.g., medicines) that are reserved and allocated to each patient. With this patient-centric view, the inventory of medicines is targeted at satisfying the needs of all patients without too much surplus stock. Two forecasting models are established to integrate patients' demographic and hospitalization information into the inventory control strategies. The first model predicts the patients' total medicine consumption based on their demographic and initial hospitalization information, while the second model updates the patient length of stay, leveraging their usage of resuscitation medicine and surgical-related consumables. Based on the 2-year data from inpatients that were admitted to eighteen hospitals in a south-eastern China city, it was demonstrated that the incorporation of medical information from patients does contribute to an accurate forecast of the pharmaceutical demands and leads to a more balanced inventory, considering the complement and substitute relationship of the different categories of medicines. This incorporation of patient information suggests that patient-centric FM thinking can potentially guide more coordinated supply chains and inventories, and better-informed operation and maintenance decisions on the basis of the anticipated length of stay for admitted inpatients.

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