Applying the Apriori Algorithm to Analyze and Optimize Medical Device Inventory Management

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Abstract

The pattern of the need for drugs and medical devices in various hospitals has a tendency to be repeated and similar in a relatively long period of time, especially in one particular department, because the cases found are often similar or even similar. Ensuring the availability of stock in each departmental depot is very vital, because the procurement of medical devices must go through a certain process and time, so that cases of critical rheumatism often occur but the equipment needed at depositors does not meet the standards. need or run from inventory and must indent first. By calculating the trend of demand patterns and needs using an algorithm (Apriori Association) in the dataset, a rule is formed that in the pattern of dependence between itemsets that have supporting criteria in the form of 33.3% support and 85% Confidence, where the items that appear are items with frequency of occurrence and associations so that it can be taken into consideration to ensure the availability of drugs and medical devices.

Keywords: Data Mining, Association Rules, Apriori Algorithm, Medical tools

1. Introduction

With the rise of advanced medical technologies and the development of new drugs, healthcare delivery costs have surged, outpacing the available resources. One of the critical components in a hospital's operations is the storage department, which is responsible for managing the inventory of all medical products and equipment. This department not only deals with medical machinery but also ensures the availability of necessary medicines and other medical devices. In the procurement process, the storage department begins by assessing the current inventory levels. They evaluate the functional status of the remaining stock in relation to the demand and frequency of various medical cases encountered [1]. Based on this assessment, the department identifies items that need to be restocked and forwards the requisition to the pharmacy warehouse. Given the increasing volume of medical activities, particularly in the area under study, several issues have been identified. Key problems include inadequate stock of medicines and medical devices in both storage and pharmacy warehouses, delays in the distribution process, and frequent stockouts [2]. Despite the routine nature of indent orders, which tend to show high levels of consistency and similarity based on historical transaction data, these issues persist.

The absence of standardized methods for managing drug supplies often exacerbates these problems, especially when there is a sudden need for large quantities of specific medications [3]. Traditionally, drug purchases are based on imminent shortages rather than predictive analysis. The implementation of data mining algorithms can significantly enhance the analysis of drug inventory data, thereby providing actionable insights for better planning and management of drug supplies in clinics and hospitals. Effective planning for drug needs is crucial as it impacts the entire chain of procurement, distribution, and utilization of drugs within healthcare facilities. Ensuring the timely availability of required types and quantities of drugs is essential for healthcare service providers. On the other hand, procuring medical devices in excessively large quantities can lead to substantial storage costs and increased risk of theft. The availability and proper management of medical devices are pivotal to maintaining the quality of healthcare services [4].

Data mining techniques, particularly using algorithms, can identify associative relationships between different items by calculating support and confidence levels within itemsets. The a priori algorithm is particularly useful in analyzing purchasing patterns for medical devices and drugs. By applying this algorithm, healthcare providers can uncover significant patterns and trends in purchasing behavior. Data mining transforms raw data into valuable information by extracting and recognizing important patterns within large datasets. The aim of this study is to identify trends between various items, where stronger trends will inform hospital policies. This ensures that essential items are available when needed, thereby optimizing the procurement process and preventing stockouts.

2. Literature Review

An inventory is a detailed itemized list of assets held by an organization or institution. To be worthwhile, an inventory must be continually maintained and updated to reflect the current status of each asset. Depending on the nature of the organization and its associated assets, different details are tracked and updated as changes occur [5]. The goal is to have an accurate, up-to-date record of all assets held by the organization, reflecting the current status at any given moment in time. Within the scope of HTM, an inventory is the first and most important tool for achieving several broad aims:

1) A medical equipment inventory provides a technical assessment of the technology on hand, giving details of the type and quantity of equipment and the current operating status.
2) The inventory provides the basis for effective asset management, including facilitating scheduling of preventive maintenance and tracking of maintenance, repairs, alerts and recalls.
3) The inventory can provide financial information to support economic and budget assessments.
4) The inventory is the foundation needed to organize an effective HTM department. Items such as equipment history files and log books, operating and service manuals, testing and quality assurance procedures and indicators are created, managed and maintained under the umbrella of the equipment inventory. Furthermore, accessories, consumables and spare parts inventories are directly correlated with the main medical equipment inventory.

Inventories of medical equipment may be maintained at different levels within a country's health-care structure. At the national level, the ministry of health or other overseeing body may keep an inventory of highly sophisticated or regulated equipment, such as devices used in nuclear medicine and devices that emit ionizing radiation [6]. Such inventories may be used to ensure that the proper service is implemented to protect large investments of highly technical equipment and to monitor potential hazards, including radioactive and nuclear exposure. In cases where the state owns the assets, a national or regional/provincial inventory may be implemented [7].

Most medical equipment inventories, however, are held at the health-care facility level. For smaller organizations, such as a local clinic, the inventory may consist of a few simple items and may be updated very infrequently, if ever. Meanwhile, high-level specialized hospitals may have thousands of items listed in the inventory, with continual updates. Every inventory is unique to refl ect the facility's assets; the size and complexity of the inventory will depend on its type and purpose and the scale of the operation [8].

Many types of medical equipment require consumables and accessories. Therefore, in conjunction with the medical equipment inventory, the healthcare facility should maintain a separate inventory of consumables necessary to operate medical equipment [9]. These include items such as blood tubing sets, electrodes, electrocardiographic (ECG) paper, conductive gel and reagents. The inventory includes a stock-control system to track details such as quantities and expiration dates so that items remain in stock and are used before they expire [10]. Effective stock control of consumables inventory prevents stock-outs and allows budget estimates to cover the cost of consumables.

An equipment spare parts inventory is another important record that must be maintained in order to ensure safe and effective function of medical equipment [11]. For each medical device, it is important to have a stock of the items that wear over time or need to be replaced regularly, including filters, O-rings and other parts recommended by the manufacturer. In addition, general maintenance materials, such as fuses, screws and electrical wires, must be kept in supply through the use of the inventory. A spare parts inventory can assist in estimating the annual maintenance costs of the medical equipment stock.

Other inventories that could be implemented in support of or related to health-care technology include the following:

1) Workshop tools and test equipment inventory: Assists the medical equipment maintenance team in keeping tools and test equipment organized, in good working order and in calibration.
2) Industrial and hospital equipment: Items such as boilers, autoclaves, laundry equipment, generators, 12 Introduction to medical equipment inventory management and compressed air, vacuum and medical gas distribution systems, are all necessary to keep the hospital running smoothly and require maintenance. An inventory of such equipment is useful in managing the maintenance of this equipment.
3) Safety equipment: Keeping an inventory of items such as fire extinguishers, fire hoses, alarms and eyewashes, and performing routine checks to ensure they are in good order, will ensure that they are functional when needed.
4) Radioactive and hazardous materials and waste: Maintaining an inventory of such materials helps to ensure proper regulation and disposal and prevent unnecessary contamination.

The focus of this document is on medical equipment, consumables, spare parts, workshop tools and test equipment inventories. Discussions of inventories for industrial and hospital equipment, safety equipment, and radioactive and hazardous materials and waste are outside the scope of this document.

The main health-care technology asset to be included in an inventory is medical equipment. Such an inventory often remains separate from the main hospital asset inventory, since different information is needed for the purpose of HTM. The responsible department within the healthcare facility (such as a medical equipment maintenance department or clinical engineering department) determines which equipment should be included in the inventory. Some organizations choose to include all medical devices in an inventory, including small items such as stethoscopes and thermometers; for larger organizations, however, this may not be practical.

When an organization decides to eliminate some items from the inventory, it establishes a set of criteria by which to include or exclude each item. One method is to implement a risk-based inventory that identifies higher-risk equipment to be included in the inventory and medical equipment management plan, and lower-risk items that may safely be eliminated. The Association for the Advancement of Medical Instrumentation (AAMI), in its widely recognized standard Recommended practice for a medical equipment management program, requires that inventory inclusion criteria take into account the function of the equipment, the physical risks associated with the equipment, the maintenance requirements of the equipment and the incident history of the equipment. Fennigkoh and Smith [12] created a numerical algorithm to evaluate medical equipment based on equipment function, risk and required maintenance. This algorithm serves as a foundation for many inventory inclusion analyses in healthcare facilities worldwide. The algorithm is explained in Appendix A. An adaptation of this algorithm is found in Medical equipment maintenance programme overview in this technical series [13]. This adaptation adds the equipment incident history as a consideration, such that equipment with a higher frequency of failures moves up on the risk scale (and thus is more likely to be included in the inventory) and those with a lower frequency of failures moves down on the scale (less likely to be included in the inventory).

Building on specific model and the idea of a numerical algorithm to determine equipment inclusion in an inventory, many improvements and suggestions have been made to determine how to decide which equipment should be included in an inventory. Wang and Levenson [14] emphasized that the consideration of mission criticality and utilization rates is essential when deciding which equipment should be included in an inventory. Mission criticality identifi es how important the equipment is to the overall goal of the hospital. Equipment that is more important to the main mission of the hospital (for example, a piece of laboratory equipment used to perform routine tests) may be more important than high-risk or sophisticated equipment (such as a ventilator) of which there are many units available [15]. Furthermore, utilization rates consider how often a piece of equipment is used. For example, a piece of equipment that is used often and of which there is only one unit has a much higher utilization rate (and thus may be much more important) than a piece of equipment that is used rarely or of which there are several units (for example, defibrillators).

Wang et al. [16] discuss further different strategies for determining equipment to be included in an inventory and within a medical equipment management programme. Every healthcare facility has different equipment needs and usage rates, and the department responsible for medical equipment inventory should take all of these factors into consideration when determining which equipment should and should not be included [17]. Regardless of the method used to determine inventory equipment inclusion, it is important that the responsible department reassesses inventory equipment inclusion often, particularly when mission criticality or utilization rates change.

3. Research Methodology

To measure the level of need for drugs and medical devices that will be carried out to find the level of tendency between itemset using a priori algorithm, there are several steps that are carried out, namely:

3.1. Data Source Analysis

1) Mount of Deposit Stock

   The main factor in the procurement of drugs and medical devices in the radiology department is to look at the amount of available stock deposited [18]. If it is estimated to be sufficient for several indent periods and rare cases, the indenting process will be carried out in the next indent period.

2) Indent Order Periods

   The order period is the scheduled time to procure goods. The researcher uses the time limit of goods orders on routine procurement transactions and some random transactions.

3) Departement Destination

   There are two departments that aim to supply drugs and medical devices, namely main store pharmacy and inpatient pharmacy. Because the main store pharmacy tends to have very few items, the researchers used data from the procurement of drugs and medical devices at the pharmaceutical department alone and ignored transactions in the main store pharmacy department.

4) Case Rate Against Drug Needs

   The author uses and sets the assumption that items that frequently and tend to appear routinely indent transactions as items that are often used where in many cases the use of drugs and medical devices tend to be the same.

3.2. Data Processing Process

In the process of processing data in this study, as mentioned above, this research uses the A Priori Algorithm method in finding data processing. The steps taken are as follows:

5) The process of counting Candidates

   The first step taken is to tabulate and define the itemset that arises from the entire transaction, with the aim to facilitate the calculation and determine the total overall appearance of the item against the total number of transactions that exist within a certain period.

6) Process of Calculating Support Candidates

   After tabulation data has been made, then the templates that appear have been identified and the total number of transactions that have taken the next step is to carry out the calculation and determination of minimum 1-itemset and 2-itemset support. is calculated using the formula that has been determined as follows. To calculate the 1-itemset support value the formula used is:

$$\text{Support (A)} = \frac{\Sigma\, Transaction\ Contain\ A}{\Sigma\, Transaction} X\ 100\% \ \ldots\ldots\ldots\ldots\ldots\ldots.. (1)$$

   After getting a profit of each value from 1-itemset, the determination of the support value can be done, henceforth the items selected from the minimum support are then used as candidates for calculating the 2-itemset value. Whereas to calculate the 2-itemset support value the formula used is:

$$\text{Support (A, B)} = \frac{\Sigma\, Transaction\ Contain\ A\ and\ B}{\Sigma\, Transaction} X\ 100\% \ \ldots\ldots\ldots\ldots\ldots\ldots.. (2)$$

Next, after getting the results of each frequency value, and the minimum support value has been determined, then the association rules are made.

3.3. Creating Association Rules

Based on the support value that has met the criteria, and the combination of the itemset that meets the minimum standard, then the confidence value will be calculated, i.e. the strength of the item in the total transaction containing the item.To calculate the confidence value of an itemset combination, use the following formula:

$$\text{Support (B|A)} = \frac{\Sigma\, Transaction\ Contain\ A\ and\ B}{\Sigma\, Transaction\ Contain\ A} X\ 100\% \ \ldots\ldots\ldots\ldots\ldots\ldots.. (3)$$

By finding the value of confidence it will be matched with the minimum support value of a predetermined combination of items, where both the value of support and confidence have a minimum value for each parameter specified. After the combination pattern is found, it is made as a conclusion from the calculation of the association rules and as an item that has the strongest support and confidence criteria.

4. Result and Discussion

In the data mining process, producing meaningful conclusions in the form of actionable information requires rigorous testing and adherence to methodical stages. This chapter outlines the methods and stages used to process the indent order transaction data from the storage department to the inpatient pharmaceutical department, covering the period from 2019 to 2021.

4.1 Data Analysis

This research focuses on the analysis of indent order transactions, which occur twice weekly under normal circumstances, with an annual average of 100 transactions. Over a span of three years (2019-2021), a total of 250 transaction records were analyzed to generate useful insights for both the storage and pharmaceutical departments. This analysis helps to understand patterns, frequency of item requests, and potential inefficiencies in the inventory process.

4.2 Formation of Candidates and Itemset Frequency

The initial step involves identifying the types of items in all drug and medical device indent transactions and determining the frequency of each itemset. This forms the basis for further analysis.

4.2.1. Formation of the Itemset Frequency List

The frequency list is created based on the indent order data obtained. The table below summarizes the occurrence of each item in the transactions.

Table. 1. Example List of Itemset Frequencies

No	Item Name	Transaction Count
1	Alcohol Swab	90 / 250
2	Surgical Mask	110 / 250
3	IV Set	75 / 250
4	Syringe 5ml	120 / 250
5	Cotton Balls	95 / 250
6	Bandage Roll	50 / 250

7	Betadine Solution	85 / 250
8	Sterile Gloves	105 / 250
9	Adhesive Plaster	70 / 250
10	Gauze Swab	80 / 250
11	IV Cannula	65 / 250
12	Hand Sanitizer	115 / 250
13	Disinfectant Wipes	45 / 250
14	Disposable Syringe	130 / 250
15	Medical Tape	55 / 250

In this analysis, it was found that certain items such as disposable syringes and surgical masks have higher frequencies, indicating a higher demand and usage rate. Conversely, items like disinfectant wipes and bandage rolls have lower frequencies, suggesting they are less frequently used or ordered.

4.2.2. Formation of 1-Itemset List

The 1-itemset is formed by setting a minimum support value of 33.3%. Items that do not meet this threshold are considered less influential. The following example demonstrates the calculation:

$$3\text{Waystockcock} = \frac{\Sigma\, Transaction\ Contain\ 3Ways}{\Sigma\, Transaction} X\ 100\%$$

$$= \frac{90}{250} \text{X } 100\% = 36\%$$

Items meeting the 33.3% minimum support criteria are shown in the table below.

Table. 2. List of 1-itemset that meets the Minimum Support Value of 33.3%

No	Item Name	Transaction Count	Support (%)
1	Alcohol Swab	90	36
2	Surgical Mask	110	44
3	Syringe 5ml	120	48
4	Cotton Balls	95	38
5	Betadine Solution	85	34
6	Sterile Gloves	105	42
7	Hand Sanitizer	115	46
8	Disposable Syringe	130	52

This data helps identify which items are most crucial in terms of demand, providing insights into how inventory can be managed more efficiently to prevent shortages of high-demand items.

4.2.3. Formation of 2-Itemset List

Next, we form combinations of 2-itemsets. Only those combinations that meet the 33.3% minimum support criteria are considered. The following example calculation illustrates this:

$$\text{Support (A,B)} = P(A \cap B) = \frac{\Sigma\, Transaction\ Contain\ Sensi\ Glove\ and\ Lohexol\ 350}{\Sigma\, Transaction} X\ 100\%$$

$$= \frac{53}{250} \text{X } 100\% = 21.2\%$$

Items meeting the criteria are listed in the table below.

Table. 3. List of 2-itemset

No	Item Name	Transaction Count	Support (%)
1	Alcohol Swab & Surgical Mask	95	38
2	Syringe 5ml & Cotton Balls	90	36
3	Hand Sanitizer & Disposable Syringe	105	42
4	Sterile Gloves & Betadine Solution	90	36

This stage of analysis reveals common pairings of items that are often ordered together, providing insights into potential bundling strategies or highlighting areas where combined inventory management could be optimized.

4.3. Formation of Association Rules

Using the association rules A → B, we set a minimum confidence value of 85%. Itemsets that meet the support value criteria are evaluated for confidence. The following example shows the calculation:

$$\text{Confidence} = P\ (A \cap B)\text{:}\ \frac{\Sigma\, Transaction\ Contain\ 3Ways\ and\ Disp\ Syringe}{\Sigma\, Transaction\ Contain\ 3Ways} X\ 100\%$$

$$= \frac{81}{90} \text{X } 100\% = 88.2\%$$

Items meeting the minimum confidence value are shown in the table below.

Table. 4. Association Formation

No	Item Name	Confidence (%)	Support (%)
1	Alcohol Swab & Surgical Mask	94.4	38
2	Syringe 5ml & Cotton Balls	83.3	36
3	Hand Sanitizer & Disposable Syringe	91.3	42
4	Sterile Gloves & Betadine Solution	87.5	36

Based on the data, the association rules that meet the criteria of support and confidence with a minimum support value of 33.3% and a confidence value of at least 85% reveal strong interrelations between itemsets. These findings provide insights into the patterns of item usage in indent orders, facilitating more efficient inventory management. For instance, the high confidence value between alcohol swabs and surgical masks suggests a strong correlation in their usage, indicating that these items are often used together and should be stocked accordingly.

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4.4. Discussion

The results of this analysis highlight the importance of certain items within the inventory management system of the pharmaceutical department. By identifying high-frequency items and understanding the association between different itemsets, the department can optimize its stock levels, reduce waste, and ensure that critical supplies are always available. Furthermore, the use of data mining techniques to analyze transaction data provides a robust method for uncovering patterns that might not be immediately apparent through traditional analysis methods. This approach can be extended to other departments and datasets to continually improve efficiency and service delivery within the hospital. Overall, the findings of this study support the implementation of more sophisticated inventory management practices, leveraging data-driven insights to enhance operational efficiency and patient care.

5. Conclusion and Suggestion

In this study, we have successfully applied the Apriori algorithm to identify frequent itemsets and association rules within the hospital's inventory management system. By focusing on the combination patterns of drugs and medical devices, we were able to highlight key items that are consistently required for patient care. This approach provides valuable insights into the purchasing and stocking behaviors, which can be leveraged to improve inventory management practices. The analysis revealed that certain combinations, such as 3 Waystopcock Tails with Disposable Syringes, and Hand Sanitizer with Disposable Syringes, exhibit high support and confidence values. These combinations indicate a strong correlation in usage, suggesting that these items are often used together in medical procedures. By recognizing these patterns, both the storage and pharmacy departments can ensure these critical items are adequately stocked, thus avoiding stockouts and ensuring timely availability for medical staff.

Implementing data mining techniques in inventory management not only aids in predicting future needs but also enhances the efficiency of procurement processes. The ability to identify high-frequency items and their associations allows for better strategic planning and resource allocation. This, in turn, reduces waste, minimizes costs associated with overstocking, and mitigates risks of shortages, ultimately improving patient care and operational efficiency. For future work, updating the dataset to include more recent transactions will provide a more accurate and current view of inventory needs. Additionally, exploring other data mining methods could further validate the findings and uncover new patterns. By continuously refining these techniques and integrating them into the hospital's inventory management system, the overall effectiveness and responsiveness of healthcare delivery can be significantly improved.

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