Journal of Information System and Technology Research

Journal Homepage: https://journal.aira.or.id/index.php/jistr/

Implementation of Multi-Level Association Rule Mining Based on Concept Hierarchy in Drug Transaction Analysis to Support Inventory Management

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ARTICLEINFO

Article history:

Received March 10, 2026
Accepted May 25, 2026
Available online may 31, 2026

Keywords:

Multi-Level Association Rule Mining
Drug Transaction Data
Concept Hierarchy
Inventory Planning

How to Cite:
N. K. Zahra, M. Idhom, and A. F. Adziima, "Implementation of Multi-Level Association Rule Mining Based on Concept Hierarchy in Drug Transaction Analysis to Support Inventory Management," Journal of Information System and Technology Research, vol. 5, no. 2,pp 306-317 May 2026

ABSTRACT

Drug inventory planning is a crucial aspect in logistics management in first-level health care facilities, as the availability of the right type and quantity of drugs greatly affects the quality of service and patient safety. However, in practice, there are still various problems, such as the mismatch between the amount of stock and the real need for limitations in the use of historical data on drug transactions, and the lack of optimal systems in identifying drug use patterns in a structured and data-based manner. This condition has the potential to cause stockouts and overstock, which has an impact on delays in the delivery of therapy, wasted budgets, and increased risk of expired drugs. In addition, the lack of analysis of drug use combinations also hinders more accurate decision-making in inventory planning and control. Based on these problems, this study aims to apply the Multi-Level Association Rule Mining (MLARM) method in identifying combinations of drug use based on transaction data at health facilities. The results of the study showed that *the* MLARM *method* was effective in identifying patterns of drug use associations at various levels of the hierarchy. At the drug class level, it was found that there was a relationship between hard drugs, over-the-counter drugs, and limited over-the-counter drugs which reflected the use of combinations between drug classes in health services. At the group level of therapy, the association involves analgesics, antibiotics, antihistamines, corticosteroids, and decongestants. Meanwhile, at the level of drug names, specific combinations were found, such as Mms with Kalk, Fe with Paracetamol, Ctm with Paracetamol, and Mefenamic Acid with Amoxicillin. This information can be used to support more optimal management of drug supplies and reduce the risk of *stockout* and *overstock*.

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1. INTRODUCTION

Drug stock planning is an important part of logistics management in first-level health care facilities, because the availability of sufficient and appropriate drugs greatly affects the smooth service and patient safety. Inaccurate availability can result in *stockout* and overstock, each resulting in therapy delays, budget waste, and increased risk of unused or expired drugs. Conventional stock planning approaches that rely only on historical usage recaps and average calculations are often less able to describe complex drug use patterns in daily transactions at health centers or other health facilities. In addition, another problem that often occurs is that transaction data has not been utilized optimally, so that the relationship between drugs that are often used together cannot be recognized properly. The lack of integration between data and differences in the writing of drug names are also obstacles in the analysis process, which can reduce the quality of the information produced. On the other hand, the inventory management system currently used is generally not able to support [1][2][3]. *Multi-level* drug combination pattern analysis, so the information obtained is still general and lacking in detail to support more appropriate decision-making. This condition shows the need for a more thorough analysis method and is able to explore drug use patterns more deeply, so that planning and controlling drug stocks in health facilities can be carried out more effectively.

Along with the increasing amount of drug transaction data stored in medical record information systems and pharmaceutical management, *data mining* techniques have become a potential tool to extract hidden patterns and relationships in data Data [4][5]. *Mining* is the process of processing and analyzing large amounts of data to identify hidden patterns, relationships between variables, tendencies, and meaningful information that was not known before. so that the results can be used as a support in decision-making One of the [6][7]. *Data mining* techniques that is widely used to find relationships between items in large datasets is Association Rule Mining (ARM), especially through a priori algorithm that is effective in extracting association rules from transaction data. A priori works by looking for [8][9]. *Frequent itemsets* and then forming association rules that can describe the concurrent tendency of multiple items in a transactionIn addition, research in other healthcare facilities also reports that Apriori-based ARM is effective in finding the association of medical data variables such as patient conditions and risk factors, demonstrating the potential of this technique to uncover hidden information in large-scale health datasets [10][11][12].

In previous studies, Association Rule Mining (ARM) has been widely applied to discover relationships and association patterns among items in transactional data, particularly through the use of the Apriori algorithm. The A priori method has been applied in various studies to identify patterns of drug or goods use in the health and pharmaceutical fields. For example, a study that analyzed drug output data showed the formation of dozens of association rules that could potentially be used as input in planning drug needs in health centers. In addition, another study states that ARM is able to help healthcare facilities minimize the risk of [13] *stockout* and *overstock* by utilizing a pattern of frequent combinations of goods [14]. Although traditional ARM is capable of generating item combination patterns, most research still focuses on one level of analysis, namely at the item level or drug name. This approach tends to result in specific rules but is less able to capture more general relationships such as relationships between drug therapy classes, drug classes, or other high-level categories. Information at a higher level can provide [14] more relevant strategic insights for operational decision-making and stock policy, as multilevel association rule mining that utilizes *the hierarchy concept* is able to capture relationships and patterns at various levels of abstraction in transaction data, making it more effective in helping inventory control than a single-level ARM. A previous study conducted by [15]. proposed the use of Multi-Level Association Rule Mining (MLARM) to extract association rules across different category levels within a conceptual hierarchy. The study demonstrated that MLARM was capable of identifying association patterns at multiple levels of abstraction, enabling the discovery of relationships not only at the item level but also at higher category levels. The results indicated that the generated patterns were more focused, relevant, and informative, thereby providing valuable insights to support decision-making processes.

Multi-Level Association Rule Mining (MLARM) was introduced as an extension of conventional ARM by utilizing *a hierarchy concept* in data. MLARM allows for the mining of association rules at different levels of abstraction or levels, which provides a more comprehensive and contextual picture of patterns. The application of MLARM in the inventory domain has shown that relationships between items can be analyzed not only at the most specific level, but also at the more general category level providing broader insights for stock management and strategy. By building a [16] *concept hierarchy* tree of attributes in the dataset, MLARM is able to find patterns of association at each level of abstraction so that the information obtained is more significant and focused than rules at a single *level*. This is relevant in stock and inventory management because in addition to showing the relationship between specific items, MLARM also provides insight into the relationship between categories or classes of goods that are strategic in operational decision-making and stock policies. The contribution of this research lies in the development of a drug transaction pattern analysis approach using *the Multi-Level Association Rule Mining* (MLARM) method which is able to identify association relationships at various levels of the hierarchy, so that the results of the analysis can be used as a basis for supporting decision-making in managing drug supplies more optimally and efficiently [17].

This study uses the application of *Multi-Level Association Rule Mining* (MLARM) based on concept hierarchy to analyze drug transactions at several levels so that the resulting patterns are more complete and easy to understand. The conceptual hierarchy used consists of three levels, namely drug class (Level 1), drug type or group (Level 2), and drug name (Level 3). The novelty in this study lies in the use of *Multi-Level Association Rule Mining* (MLARM) with the application of a three-level conceptual hierarchy, namely drug groups, drug groups, and drug names, in health facility transaction data. This approach is also complemented by a process of standardizing drug naming to improve consistency in the formation of association rules. Although a number of studies have proven that *Association Rule Mining* (ARM) is effective in identifying patterns of drug use combinations, the majority of these studies still apply a *single-level analysis* *approach*. This approach is able to produce detailed rules of association on a particular item, but it is not yet able to represent the relationships between drug categories at a broader level, such as drug groups and groups. As a result, the information produced is still limited and not optimal enough to support inventory planning and strategic decision-making in pharmaceutical inventory management. With this approach, the MLARM results not only describe specific drug combinations, but are also able to display relationships at the level of more relevant types of therapies and drug classes to support planning strategies and stock control priorities. Therefore, this study aims to apply Multi-Level Association Rule Mining (MLARM) based on a conceptual hierarchy to analyze drug transaction data in health facilities. The scientific novelty of this research lies in the application of a three-level conceptual hierarchy in the process of extracting association rules, as well as the inclusion of the drug name standardization stage to produce a more complete, consistent, and easy-to-understand drug combination pattern as a reference for drug inventory control [18].

2. RESEARCH METHOD

This study aims to examine the pattern of linkages between drugs contained in pharmaceutical transaction data using a data mining approach. The method applied refers to Multi-Level Association Rule Mining (MLARM) based on the hierarchy of drug concepts, so that the analysis of the relationship between items is not only carried out at the level of the drug name, but also includes the level of groups and groups of drugs. This approach is expected to produce more meaningful information and can be applied practically in supporting the planning and control of drug stocks.

2.1 Research Design

This research applies a quantitative approach with an exploratory design. The quantitative approach is used because the data analyzed is in the form of drug transaction data over a period of one month with a relatively large number of transactions, while the exploratory design aims to explore patterns of linkages between drugs that have not been clearly identified before.

The application *of association rule mining* has become a common technique in data mining to find patterns of relationships between items in a transaction database. This technique systematically identifies frequent itemsets and generates significant rules based on *support* and *confidence values*, making it particularly relevant for the analysis of relationships between items in large transaction datasets such as drug transaction data [19][20]. Extending this method by considering the conceptual hierarchy thus allows the extraction of association patterns at different levels of data abstraction. This approach offers more comprehensive insights than techniques at a single level [21].

2.2 Multi-Level Association Rule Mining

Association rule mining (ARM) is an important method in the field of data mining that aims to find patterns of relationships between items that often appear simultaneously in transaction data. This method is widely used in transactional data because of its ability to dig up hidden information and present it in the form of rules that are intuitive and easy to interpret. The rule of association is generally expressed in the form of an implicit relationship, which indicates that the existence of a set of items in a transaction increases the likelihood of an item appearing in the same transaction. With this approach, ARM not only analyzes the appearan\ce of items separately, but also emphasizes the pattern of togetherness between items in a single transaction [19].*Multi-Level Association Rule Mining* (MLARM) is a form of development of *conventional Association Rule Mining* (ARM) designed to identify patterns of interconnectedness between items at various levels of hierarchy or levels of abstraction in a data set. In contrast to the traditional ARM approach which generally only focuses on the analysis of relationships at one specific level, for example at the level of specific items such as product names or drug names, MLARM allows the analysis process to be carried out in stages through categories arranged in a *concept hierarchy* structure [22].

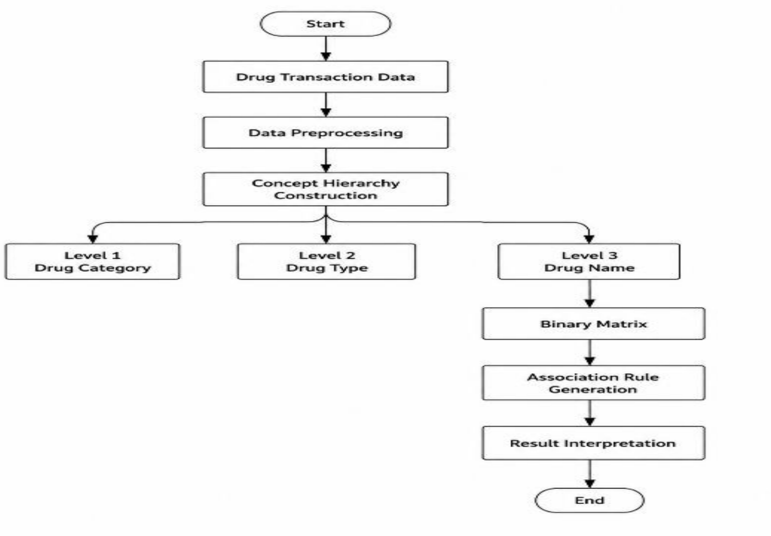

Figure 1. Research flowchart
(Source: Developed by the Author)

Figure 1. presents the flow of the research methodology applied in the use of *Multi-Level Association Rule Mining* (MLARM) to analyze drug transaction patterns. The diagram aims to describe the stages of research in a structured manner, starting from the data collection process to the interpretation stage of the analysis results. The existence of this image serves to help readers understand the flow of the data processing process and the relationship between each stage in the formation of association rules at various levels of analysis. The diagram is read from the top showing drug transaction data as research input. The data then goes through *the preprocessing data stage* before being compiled into a three-level conceptual hierarchy, namely drug groups, drug groups, and drug names as the basis for multi-level analysis. Furthermore, the data at the drug name level is converted into *a binary matrix* for the process of forming association rules, which are then interpreted to obtain supporting information in controlling drug inventory.

In general, the association rule mining process is carried out through two main stages. The first stage is the identification of *frequent itemsets*, which are combinations of items that have an appearance rate above a certain *support* threshold. The support value serves to represent the proportion of transactions that contain a combination of items, so that low-frequency combinations can be filtered from the start. The next stage is the formation of association rules from the frequent itemsets by considering the *confidence* value, which reflects the level of reliability of the relationship between the antecedent and consequential parts of a rule. These two stages allow ARM to generate relevant and significant association patterns for further analysis [22].

1. Support

Support is a measure used to determine the proportion of transactions that contain a certain combination of items compared to all transactions in the dataset. This value indicates how often a combination of items appears together in the transaction data, so combinations that have a high support value are considered a frequent pattern. In the process of association rule mining, support is a basic metric used to determine whether an itemset is worth further processing into an association rule or not [23].

$$P(A \cap B) = \frac{the\ number\ of\ transactions\ containing\ the\ item}{transaction\ amount} \quad (1)$$

$$Support\ A = \frac{the\ number\ of\ transactions\ containing\ the\ item\ A}{transaction\ amount} \quad (2)$$

After identifying the frequent 2-itemsets, their support values are determined using the following formula:

$$\text{Support (A,B)} = \frac{the\ number\ of\ transactions\ containing\ the\ item\ A\ and\ B}{transaction\ amount} \quad (3)$$

2. Confidence

Confidence is a measure used to show the level of strength of the relationship between antecedent and consequential parts in an association rule. The confidence value represents the chance of a consequent item appearing when the antecedent item has appeared first in a transaction. In other words, confidence describes how likely it is that an item will be purchased or appear at the same time after another item occurs, so this metric is used to assess the level of reliability of an association rule [24].

$$Confidence(A,B) = \frac{the\ number\ of\ transactions\ containing\ the\ item\ (A\ and\ B)}{the\ number\ of\ transactions\ containing\ the\ item\ A} \quad (4)$$

$$P(A,B) = \frac{Support\ A \cap B}{P(A)} \quad (5)$$

3. Lift Ratio

Lift Ratio is a metric used to evaluate the strength or level of interconnectedness between items in an association rule resulting from the calculation of *support* and *confidence*. This metric acts as an indicator to assess whether a rule is feasible or has practical value in the context of the relationship being disclosed. The way Elevator works is to compare the actual *confidence* value of a rule against the *expected confidence* if the two items are not interconnected. In other words, the Lift value is obtained by dividing *the confidence* of a rule by *the expected confidence*, thus giving an idea of whether the relationship occurs more often than randomly expected [25].

$$\text{Confidence P (B,A)} = \frac{the\ number\ of\ transactions\ containing\ the\ item\ (A\ and\ B)}{the\ number\ of\ transactions\ containing\ the\ item\ A} \quad (6)$$

$$\text{Expected confidence} = \frac{the\ number\ of\ transactions\ containing\ the\ item\ B}{transaction\ amount} \quad (7)$$

The lift ratio is calculated by comparing the *confidence* value of a rule to the *expected confidence*. In other words, the lift ratio value is obtained through the results of the division between *confidence* and *expected confidence* according to the formula.

$$Lift\ Ratio = \frac{Confidence}{Expected\ Confidence} \quad (8)$$

Support values help choose relevant and significant product combinations, *confidence* measures the strength of relationships between products, while *lift* determines how much value the association is compared to random odds.

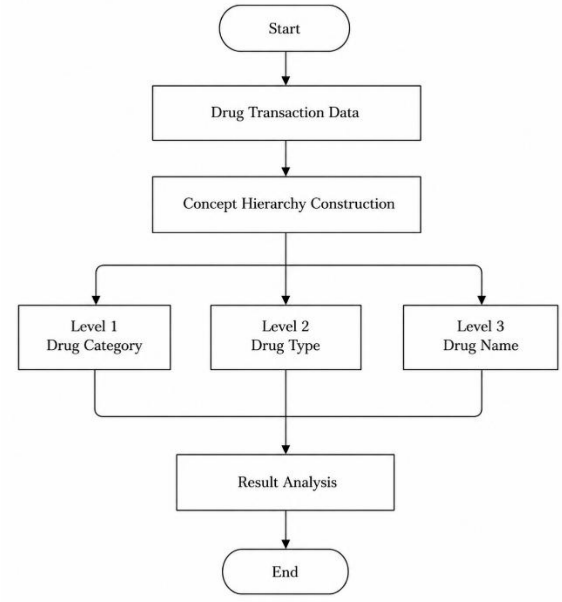

Figure 2. Mapping Hierarchy
(Source: Developed by the Author)

Figure 2. presents the flow of the application *of Multi-Level Association Rule Mining* (MLARM) in the analysis of drug transactions. This diagram serves to describe the stages of systematic analysis, starting from drug transaction data, followed by the preparation of *a concept hierarchy* into three levels, namely drug groups, drug groups, and drug names. Each level is then analyzed to produce an association pattern which is then used at the *result analysis* stage as a basis for supporting decision-making in the management of drug inventory.

In Multi-Level Association Rule Mining (MLARM), the analysis of the pattern of interconnectedness between items is carried out at several levels of abstraction based on a predetermined conceptual hierarchy. In this study, associations were analyzed at three levels, namely the drug group level, the therapy group level, and the drug name level. The drug class level is the most common level of analysis that aims to identify patterns of linkages between drug categories globally.

Furthermore, at the level of the therapy group, the analysis is carried out at a more specific level to find out the relationship between drug groups based on the similarity of their therapeutic functions. At the most detailed level, namely the drug name level, association rule mining is applied to find patterns of linkages between specific drugs that often appear together in a single transaction. This three-level approach allows for generalized to detailed association patterns, providing a more comprehensive understanding of the structure and usage trends of drugs in transaction data.

3. RESULTS AND DISCUSSION

This chapter describes the results of the implementation of the methods that have been designed in the research, starting from the data preprocessing process, the preparation of the drug concept hierarchy, the mining *of frequent itemsets* at each level, to the formation of association rules. These stages are carried out systematically to ensure that the analysis process runs in accordance with the methodological framework described in the previous chapter.

3.1. Data Preprocessing

The *preprocessing* stage is carried out to ensure that the drug transaction data used in the study is in a clean, consistent, and ready condition to be analyzed using the Multi-Level Association Rule Mining (MLARM) method. This stage is very important because the quality of the data used will have a direct effect on the accuracy and reliability of the resulting association patterns. Table 1. Displays the drug transaction data used as the basis for the analysis process. The data contains information on patient symptoms and drug therapy given in each transaction. This table is used to show the initial form of data before the association pattern analysis process, where each row represents one service transaction, while the list of drugs in the therapy column is the item that is analyzed to identify the pattern of drug use relationships.

Table 1. Dataset

No	Symptoms	Therapy
1.	Itching, coughing, cold	Amoxicillin, Cetirizin, Noza
2.	Itching all over the body	Amoxicillin, cetirizin
3.	Ear pain	Amoxicillin, chloramphenicol ear drops
4.	Low back pain, headache	Antacids, methylprednisolone
5.	Sciatica, hand cramps	Vit B complex, Chlorpheniramine Maleate

(Source: Developed by the Author)

The preprocessing stage begins with cleaning and normalizing the text (cleaning data) to ensure that drug transaction data is in a consistent format before the analysis process is carried out. At this stage, the text is normalized to the drug name contained in the therapy attributes, such as changing the entire text to capital letters, removing unnecessary spaces, and tidying up the writing format so that each item has a uniform shape. After that, drug names are standardized to overcome writing variations that often appear in the data, such as differences in spelling, abbreviations, and writing errors. Each variation of the drug name is then adjusted to a standard form of the name so that each drug is uniquely represented in the dataset. In addition, the process of eliminating duplicate drugs in one transaction is also carried out so that each type of drug only appears once in one transaction. This step is important to avoid over-counting of frequencies in the pattern mining process.

Furthermore, the cleaned and standardized therapy data is transformed into a list of transactions by separating each drug name based on a specific separator so that each transaction is represented as a collection of drug items. After the transaction list is formed, a conceptual hierarchy mapping is carried out to group each drug into three category levels, namely drug class, drug therapy type or group, and drug name. The next stage is to form a *binary matrix* for each level of the concept hierarchy, where each row represents a single transaction and each column represents a specific drug item or category of drug. The formation of a *binary matrix* is carried out after drug transaction data goes through the stages of cleaning, standardization, and mapping into a conceptual hierarchy. This transformation aims to transform transaction data that was originally in the form of a list of drug items into a structured representation that can be processed by a pattern mining algorithm in the Multi-Level Association Rule Mining (MLARM) method. In *a binary matrix*, each row represents a single transaction, while each column represents an item or category of medicine. The values used in the matrix are boolean values, i.e. *True* and *False*, where *the value of True* indicates that the item appears in the transaction, while the value *of False* indicates that the item does not appear in the transaction. Using this representation, the frequency of occurrence of items can be calculated systematically, making it easier to search for *frequent itemssets* and establish association rules at the next stage of analysis.

At Level 1 of the Drug Class, the transaction data is converted into a binary matrix based on *True/False values* based on the category of the drug class that describes the classification of drug regulations. Categories at this level include over-the-counter drugs, limited over-the-counter drugs, and hard drugs. Each transaction will be given *a True* value in the drug class column if there is at least one drug included in that group. On the other hand, if there is no drug from this group, the value given is *False*. This representation allows the analysis to determine the relationships between drug classes that often appear simultaneously in a healthcare transaction.

Table 2. Binary matrix level 1

Transaction Id	Over-the-counter drugs	Limited over-the-counter drugs	Hard Drugs
1	False	True	True
2	False	True	True
3	False	False	True
4	True	False	True
5	True	True	False
.....	.....	.....	.....
596	True	False	True

(Source: Developed by the Author)

At Level 2 Types or Groups of Drug Therapy, the binary matrix is formed based on the category of functions or uses of drugs in medical therapy. The categories used at this level include various therapy groups such as analgesics, anxiolytics, antacids, anti-gout, antibiotics, and other therapy groups contained in the dataset. At this stage, each drug contained in the transaction is first mapped into its therapy group. Furthermore, True is given in the therapy group column if in a transaction there are drugs that are included in the therapy group. On the other hand, a value of False is given if the therapy group does not appear in the transaction. This representation allows for the analysis of relationships between types of drug therapies that are often used simultaneously in the treatment process.

Table 3. Binary matrix level 2

Transaction Id	Anagelsik	Anxiolytic	Antacids	Anti-Taste	.....	Antibiotics
1	False	False	False	False	.....	True
2	False	False	False	False	.....	True
3	False	False	False	False	.....	True
4	False	False	True	False	.....	False
5	False	False	False	False	.....	False
.....	.....	.....	.....	.....	.....	.....
596	False	False	False	False	.....	False

(Source: Developed by the Author)

Meanwhile, at Level 3 Drug Name, the binary matrix is formed based on the most specific item, namely the name of the drug contained in the transaction. Each column on the matrix represents one type of drug, for example allopurinol, alprazolam, ambroxol, amlodipine, to amoxicillin and various other drugs contained in the research dataset. Each transaction will be given a value of 1 in the column of a particular drug if the drug is included in the transaction, and a value of 0 if the drug does not appear. This level allows for a more detailed analysis of drug combination patterns because the relationships obtained are derived from specific drug items.

Table 4. Binary matrix level 3

Transaction Id	Allopurinol	Alprazolam	Ambroxol	Amlodipin	.....	Amoxicillin
1	False	False	False	False	.....	False
2	False	False	False	False	.....	False
3	False	False	False	False	.....	False
4	False	False	False	False	.....	False
5	False	False	False	False	.....	False
.....	.....	.....	.....	.....	.....	.....
596	False	False	False	False	.....	False

(Source: Developed by the Author)

By forming a binary matrix at three levels of the concept hierarchy, this study can analyze the pattern of drug relationships at various levels of abstraction. Analysis at higher levels such as drug classes and therapy groups can provide a more general and strategic picture of relationships, while analysis at the drug name level provides more specific information about drug combinations that often appear in transactions. The representation of data in the form of a binary matrix is then used as input in the process of mining frequent itemset and forming association rules using a priori algorithm in the Multi-Level Association Rule Mining method.

3.2. Multi-Level Association Rule

Before the association rule generation process is carried out, it is necessary to evaluate the quality of the generated rules to ensure that the identified patterns exhibit meaningful relationships. As reported in previous studies [26], the quality of association rules is commonly evaluated using the measures of support, confidence, and lift. Support indicates the frequency of occurrence of an item combination within transactional data, confidence measures the reliability of the relationship between items, while lift is used to assess the strength of the association. A lift value greater than 1 indicates a positive relationship between items, suggesting that the generated rule is valid and relevant for supporting decision-making processes, particularly in drug inventory planning and control.

At this stage, the process of mining association rules is carried out by applying *the Multi-Level Association Rule Mining* (MLARM) method. The analysis is carried out in stages according to the hierarchical structure of the drug concept that has been designed, namely Level 1 (drug class), Level 2 (drug type), and Level 3 (drug name). This multi-layered approach allows for the exploration of patterns of interdrug linkages from the most detailed levels to the more general levels. Each rule generated is then evaluated using *support* and *confidence* parameters. The *support value* represents the degree to which a combination of items appears in the overall transaction, while the *confidence* indicates how strong the relationship between the items is in an association rule.

Table 5. Level 1 Association

No	Antecedent	Consequent	Support	Confidence	Lift
1	Hard drugs	Limited over-the-counter drugs	0.513	0.761	1.278
2	Limited over-the-counter drugs	Hard drugs	0.513	0.862	1.278
3	Over-the-counter drugs limited, Over-the-counter drugs	Hard drugs	0.200	0.799	1.184
4	Hard drugs, Over-the-counter drugs	Limited over-the-counter drugs	0.200	0.676	1.135

(Source: Developed by the Author)

Rule Results Based on the results of the implementation of Multi-Level Association Rule Mining at the drug group level, several association rules were obtained that show the existence of a relationship between drug groups in health service transactions. Table 5. Indicates the relationship between the items in the *Antecedents* and *Consequent* columns. For example, in the Hard Drugs → Over-the-Counter Drugs rule, *a support* value of 0.513 indicates that the combination appears in 51.3% of all transactions, while a *confidence* of 0.761 indicates that 76.1% of transactions containing hard drugs also contain limited over-the-counter drugs. An *elevator* value of 1.278 indicates a positive association relationship because it is worth more than 1. The same interpretation applies to the rest of the rule lines. This shows that in the health service process, administering drugs to patients often involves a combination of drugs from several different groups according to the needs of therapy.

In addition, a relationship was also found between the combination of hard drugs and over-the-counter drugs with limited over-the-counter drugs, as well as the relationship between limited over-the-counter drugs and over-the-counter drugs with hard drugs. This pattern shows that in some transactions there is the use of drugs from more than one group at the same time. These findings provide an idea that combinations between drug classes are common in the process of providing therapy to patients. Information about the pattern of the emergence of these drug groups can be used as a consideration in planning and controlling drug supplies, so that health facilities can ensure the availability of drugs from various groups that are often used simultaneously.

Table 6. Level 2 associations

No	Antecedent	Consequent	Support	Confidence	Lift
1	Analgesics, Corticosteroids	Antibiotics, Antihistamines	0.064	0.644	4.362
2	Analgesics, Antibiotics, Corticosteroids	Antihistamines	0.064	0.826	4.244
3	Analgesics, Corticosteroids	Antihistamines	0.065	0.661	3.396
4	Antihistamines, Corticosteroids	Analgesics, Antibiotics	0.064	0.826	2.896
5	Analgesics, Antihistamines, Corticosteroids	Antibiotics	0.064	0.974	2.135
6	Antihistamines, Corticosteroids	Antibiotics	0.074	0.957	2.096
7	Analgesics, Antihistamines	Antibiotics	0.116	0.908	1.989
8	Decongestant	Antibiotics	0.104	0.886	1.941
9	Antibiotics, Antihistamines, Corticosteroids	Anagelsik	0.064	0.864	1.812
10	Antihistamines, Corticosteroids	Anagelsik	0.065	0.848	1.779

(Source: Developed by the Author)

The interpretation of table 6. is carried out by analyzing the relationship between *antecedents* and *consequents* on each resulting association rule. As an illustration, the rule of *analgesics, corticosteroids → antibiotics, antihistamines* with a *support* value of 0.064 showed that these combinations were present in 6.4% of all transactions. *A confidence* value of 0.644 indicates that 64.4% of transactions containing analgesics and corticosteroids were also followed by antibiotics and antihistamines. In addition, *the lift* value of 4.362 indicates a positive association and is quite strong because the value exceeds 1. A similar interpretation applies to the other association rules in the table. This pattern suggests that in some medical conditions, patients may receive several types of medications simultaneously to manage the various symptoms that arise. These findings provide an idea that the use of drugs in healthcare often involves a combination of different therapy groups. Information about the relationship patterns between these types of drugs can be used as a basis for consideration in planning and controlling drug inventory, so that health facilities can ensure the availability of drugs that are often used simultaneously in patient services.

Table 7. Level 3 associations

No	Antecedent	Consequent	Support	Confidence	Lift
1	Mms(Supelmen)[Over-the-counter drug]	Kalk(Supelmen)[Over-the-counter drug]	0.057	0.944	4.576
2	kalk(Supelmen)[Over-the-counter drug]	Fe(Supelmen)[Over-the-counter medication]	0.149	0.724	4.356
3	Fe(Supelmen)[Over-the-counter medication]	Paracetamol(Analgesic)[Over-the-counter drug]	0.149	0.899	4.356
4	C(Antihistamines)[Over-the-counter drugs limited]	Paracetamol(Analgesic)[Over-the-counter drug]	0.059	0.875	4.206
5	Mefenamic acid(Analgesic) [Limited over-the-counter medication]	Amoxicillin(Antibiotic) [Hard drugs]	0.099	0.766	3.624

(Source: Developed by the Author)

Interpretation of the association pattern at level 3 indicates that the association between drug items is dominated by the supplement and analgesic groups. The kalk item is recorded as the most frequently appearing drug in the rules of association, both in combination with Mms and Fe, leading to a tendency to use several types of supplements simultaneously in a single transaction. In addition, Paracetamol also shows a fairly high frequency of occurrence in association patterns, particularly in combination with Fe and Ctm, thus reflecting its role as a commonly used item alongside other drugs. Other association patterns also show a relationship between Mefenamic acid and Amoxicillin, which represents a combination of analgesic drugs and antibiotics. In general, findings at this level illustrate that drug transaction patterns are formed more from a combination of supplements, pain relievers, and drugs used to treat certain symptoms.

These findings indicate that prescribing patterns are not solely focused on primary treatment but also involve supportive therapies that contribute to the overall patient care process. The high frequency of associations among Kalk, MMS, and Fe suggests that supplement use plays a significant role in the analyzed drug transactions. This condition reflects a relatively high demand for supplement-related medications within healthcare services.

From the perspective of inventory management, medications that frequently appear in association rules tend to exhibit stable and recurring demand patterns. Consequently, the knowledge generated through MLARM can provide valuable insights for designing more effective inventory control strategies. Drugs such as Kalk, Fe, Paracetamol, and MMS should receive greater attention in inventory planning and safety stock determination, as they not only demonstrate high utilization rates but also commonly occur together in prescriptions. This indicates that an increase in demand for one medication may be accompanied by a corresponding increase in demand for related drugs. Therefore, maintaining adequate safety stock levels for strongly associated medications can help mitigate demand variability and reduce the likelihood of stockouts. In addition, the identified association patterns can support the establishment of appropriate reorder points, allowing replenishment activities to be initiated before inventory levels become critically low. By incorporating these patterns into procurement planning, healthcare facilities can improve the accuracy of inventory decisions, reduce the occurrence of excess or insufficient stock, and enhance the overall efficiency and effectiveness of pharmaceutical inventory management.

4. CONCLUSION

Based on the results of the implementation of *Multi-Level Association Rule Mining* (MLARM) on drug transaction data, it can be concluded that this approach is able to reveal patterns of interconnectedness between drug items at several levels of the conceptual hierarchy, including the level of drug groups, therapy group levels, and the level of drug names in detail. At the first level, the results of the analysis showed that there was a fairly strong association relationship between the hard drugs, over-the-counter drugs, and limited over-the-counter drugs. At the second level, the pattern of associations formed shows the connection between drug therapy groups, such as analgesics, antibiotics, antihistamines, corticosteroids, and decongestants. This relationship reflects that the treatment of certain medical conditions often requires the use of several therapy groups simultaneously to address the various symptoms and indications of the disease experienced by the patient. Thus, the combination between these drug groups illustrates a therapeutic pattern that is commonly applied in health services. Lastly at the third level, the results of the analysis resulted in a more specific association pattern as it focused on the level of the drug name. Some of the combinations identified include Mms with Kalk, Fe with Paracetamol, Ctm with Paracetamol, and Mefenamic Acid with Amoxicillin. This pattern shows a tendency to use certain drug items simultaneously in a single transaction, which represents the practice of administering combination therapy based on the patient's treatment needs.

In general, the association pattern resulting from the analysis at three levels of hierarchy provides useful information in supporting the management of drug supplies in health care facilities. Data on drug combinations that often appear simultaneously in transactions can be used as a reference in the procurement planning process, determining inventory priorities, and controlling stocks to be in line with actual service needs. By knowing the relationship between drugs that are often prescribed at the same time, pharmacy managers can estimate drug needs more accurately, so that the potential for *stockout* that can interfere with services and overstock that risks causing cost wastage and drug expiration can be suppressed.

In addition to playing a role in supporting inventory control, the results of the association's analysis also have benefits in improving operational efficiency in drug storage management. Medications that show a high level of interconnectedness or have a tendency to be used concomitantly in the service can be placed in storage locations adjacent to each other to speed up the process of taking medications during prescription preparation. The implementation of this strategy has the potential to help pharmacists in improving the speed and accuracy of service to patients. In addition, storage arrangements based on drug association patterns can encourage the creation of a more structured, efficient, and adaptive inventory management system to the needs of health services.

This study has several limitations that should be considered. The dataset used in this study consisted of only 596 drug transaction records collected from a single healthcare facility, which may limit the generalizability of the findings to other healthcare settings. In addition, the analysis focused solely on identifying association patterns and did not incorporate future drug demand forecasting. Therefore, future research is recommended to utilize larger datasets and involve multiple healthcare facilities to improve the robustness and applicability of the results. Furthermore, integrating Multi-Level Association Rule Mining with forecasting techniques may provide a more comprehensive approach to supporting drug inventory planning and management.

5. ACKNOWLEDGEMENTS

The author expressed his gratitude to the health service facilities for providing access to the drug transaction data used in this study. Gratitude was also conveyed to the supervisor for his direction and guidance during the research process. In addition, the author appreciates the *Journal of Information Systems and Technology Research* as a forum for scientific publications that provide an opportunity to disseminate the results of this research.

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