Original Scientific Article Journal of Decision Analytics and Intelligent Computing
Vol. 2 issue 1, (2022) 1-11 https://doi.org/10.31181/jdaic10028042022c

Mining of association rules for treatment of dental diseases

Santonab Chakraborty[1], Bivash Mallick[1] and Shankar Chakraborty[2*]

[1] Industrial Engineering and Management Department, Maulana Abul Kalam Azad University of Technology, West Bengal, India

[2] Department of Production Engineering, Jadavpur University, Kolkata, India

E-mail: s_chakraborty00@yahoo.co.in

Received: December 26, 2021.
Accepted for publication: March 21, 2022.
Published: April 28, 2022.

Abstract

A prior knowledge regarding the effectiveness of each of the medicines prescribed by a physician would be quite helpful to a patient for rapid recovery from a particular disease. In this paper, an attempt is put forward to develop the related association rules for understanding the roles of different types of medicines prescribed for treatment of dental diseases, especially tooth pain (odontalgia/dentalgia) and swelling of tooth (pericoronitis). 75 patient cases from a dentist are analyzed to determine the average number of different types of medicines prescribed, average number of medicines and average cost of treatment, and to mine the corresponding association rules. It is observed from 1-item dataset that antibiotic#1 is the most preferred medicine, followed by antiseptic. Similarly, the 2-item dataset shows that the most preferred combination on medicines is {antibiotic#1, antiseptic}, followed by {antibiotic#1, anti-reflux}. Among all the association rules developed, the rule (If antibiotic#1 and antibiotic#2 and antiseptic, then anti-reflux) appears with the maximum strength.

Keywords: Data mining; Association rule; Dental disease; Support; Confidence.

1. Introduction

Data mining is the analysis step of knowledge discovery in database (KDD) conceptualized to extract interesting (non-trivial, implicit, previously unknown and useful) information or patterns from large data repositories while transforming them into understandable structures for further use (Han et al., 2012). With the availability of huge volume of data and high speed computational facilities, the need of data mining techniques has been significantly increased in information related applications for effective managerial decision making. The application of data mining tools mainly includes machine learning, cluster analysis, regression analysis and neural networks. Based on a given training dataset, neural networks and regression analysis both create a single model using a predetermined set of features. On the other hand, a machine learning algorithm generates a number of models, usually in the form of decision rules, to highlight the predominant relationships between the input features and the decision. In cluster analysis, based on some specific features, similar objects are grouped into one cluster and dissimilar objects are segregated into another cluster. In machine learning algorithm, the set of features included in each rule can be independent from all other rules, similar to the result generated by cluster analysis. The developed models (rules) are explicit and are readily expressed in English to be easily understood by the decision makers. Sometimes, the contents of datasets with qualitative and categorical information are difficult to interpret unless the information is converted into simple rules. The rule extraction algorithms in data mining are designed to identify patterns in such datasets, while articulating them as decision rules (Kusiak *et al.*, 2000; Wang, 2007).

The concept of association rule mining aims to find out frequent patterns, interesting correlations, associations or causal structures among sets of items in the transaction databases, relational databases or other data repositories (Jaiswal & Agarwal, 2012). They are being widely used in various areas, like telecommunication networks, risk and market management, inventory control etc. (Bala, 2009; Bala *et al.*, 2010; Adewole *et al.*, 2014; Agarwal & Mittal, 2019). Extracting association rules in healthcare sector also helps in identifying associations among various diseases, diseases and symptoms, diseases and medicines (Mandave *et al.*, 2013; Kulkarni & Mundhe, 2017; Lakshmi & Vadivu, 2017; Arul Valan & Baburaj, 2020). The motivation behind the development of association rules is market basket analysis which deals with the contents of point-of-sale transactions of large retailers with co-occurrence of items in a dataset. In a given transaction with multiple items, it attempts to develop rules that identify how or why different items are often bought together (Shaukat *et al.*, 2015; Mukherjee *et al.*, 2018).

Involving the use of machine learning tools, the association rules, as the name proposes, are straightforward 'If-Then' statements to analyze frequently occurring patterns in a dataset or discover inherent relationships between independent and dependant variables in a dataset. These rules are suitable for non-numeric, categorical data, developed just by simple counting. An association rule has two components, i.e. an antecedent (if) and a consequent (then) (Kotsiantis and Kanellopoulos, 2006; Kaur, 2014; Meenakshi, 2014). An antecedent is an item found within the dataset, whereas, a consequent is an item observed in combination with the antecedent. The 'If-Then' expression thus attains a form, like 'If *condition* Then *conclusion*'. These rules are generated while searching the dataset for the occurrence of frequent 'If-Then' patterns, and the most important relationships are later validated by the support and confidence criteria (Thakur & Shah, 2012; Gupta & Chauhan, 2013).

Support and confidence are the two primary parameters of association rules. Support indicates how frequently the items appear in the dataset, whereas, confidence is the measure of the number of times the 'If-Then' statements are found true. They identify the relationships and rules generated by analyzing data for frequently used 'If-Then' patterns. Association rules need to satisfy a user-specified minimum support and minimum confidence at the same time (Sadoyan *et al.*, 2006). Let D be the set of transactions where each transaction T in D represents a set of items in I. Suppose there are two sets of items, A and B, then an association rule takes the form 'If A Then B' ($A \Rightarrow B$), where the antecedent A and consequent B are proper subsets of I, and A and B are mutually exclusive. The support (s) for a particular association rule $A \Rightarrow B$ is the proportion of transactions in D that contain both A and B.

$$\text{Support} = P(A \cap B) = \frac{\text{Number of transactions containing both } A \text{ and } B}{\text{Total number of transactions}} \tag{1}$$

On the other hand, confidence (c) of the association rule $A \Rightarrow B$ is a measure of accuracy of the rule, determined by the percentage of transactions in D containing A that also contain B.

$$\text{Confidence} = P(B/A) = \frac{P(A \cap B)}{P(A)} \tag{2}$$

Thus, framing of association rules consists of two sub-problems. The first sub-problem deals with finding out those item sets whose occurrences exceed a predefined threshold in the dataset. They are called frequent or large item sets. In the second sub-problem, the association rules are generated while deleting the last item in the antecedent and inserting it to the consequent, and the confidences of the new rules are further checked to determine the interestingness of them. This process iterates until the antecedent becomes empty. The first sub-problem can also be divided into two elements, i.e. candidate item sets generation process and frequent item sets generation process. The item sets whose support exceed the support threshold are called frequent item sets, whereas, the item sets that are expected to be large or frequent are candidate item sets. As it is sometimes impossible for the end users to comprehend large number of complex association rules, it is thus always beneficial to frame the corresponding association rules from candidate item sets. The framing of decision rules is exhibited in Figure 1.

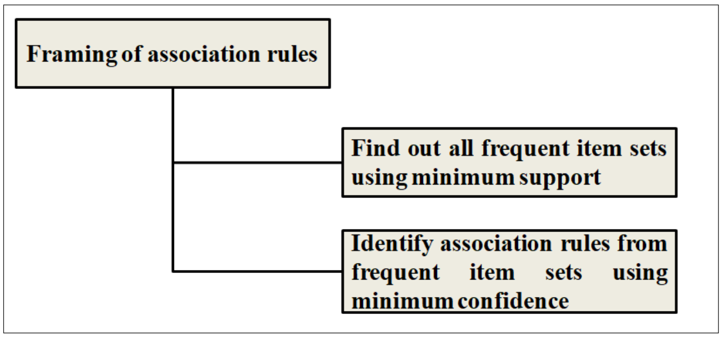


Figure 1. Framing of association rules

It has already been mentioned that in healthcare sector, extraction of association rules helps in identifying associations among various diseases, diseases and symptoms, and diseases and medicines. This paper thus aims in framing association rules for the treatment of dental diseases, mainly tooth pain (odontalgia/dentalgia) and swelling of tooth (pericoronitis), based on the medicines prescribed by a physician. Mining of these rules would help the patients in identifying the effectiveness of the medicines through causal structures depicting the relationships between symptoms and medicines prescribed.

2. Analysis of the data

In order to develop the corresponding association rules for dental problems, the help of a dentist was sought, and the medicines prescribed by him for 75 cases (66 adult patients and 9 child patients) during a time span of one month were analyzed. The medicines were mainly prescribed for the treatment of tooth pain (odontalgia/dentalgia) and swelling of tooth (pericoronitis). Tooth pain can occur due to several reasons, like tooth decay, abscessed tooth, broken tooth, damaged filing, infected gums, eruption etc. On the other hand, gingivitis, malnutrition, infection etc. may be the reasons for swelling of tooth. It is observed that the concerned dentist never prescribed those medicines with respect to their generic names. To have a better understanding on the role of each of the medicines in curing dental diseases, those medicines are first converted into their generic names along with their prescribed quantities and involved costs. In Table 1, those medicines are classified in different types, and it is noticed that seven types of medicines, i.e. antibiotic#1, antibiotic#2, anti-inflammatory, analgesic, anti-reflux, antiseptic and anti-pyretic are mainly prescribed for treatment of tooth pain and swelling of tooth. An antibiotic is an antimicrobial substance active against bacterial infections. It either kills or inhibits the growth of bacteria by preventing them from forming the bacterial protective covering (cell wall) which is needed for them to survive. Anti-inflammatory medicines are non-steroidal drugs that help in reducing inflammation and relieving pain. On the other hand, an analgesic helps to relief pain. An anti-reflux medicine is often prescribed for the treatment of gastroesophageal reflux by stopping or slowing down the growth of micro-organisms. An anti-pyretic medicine reduces fever.

Table 1. Different types of the medicines prescribed

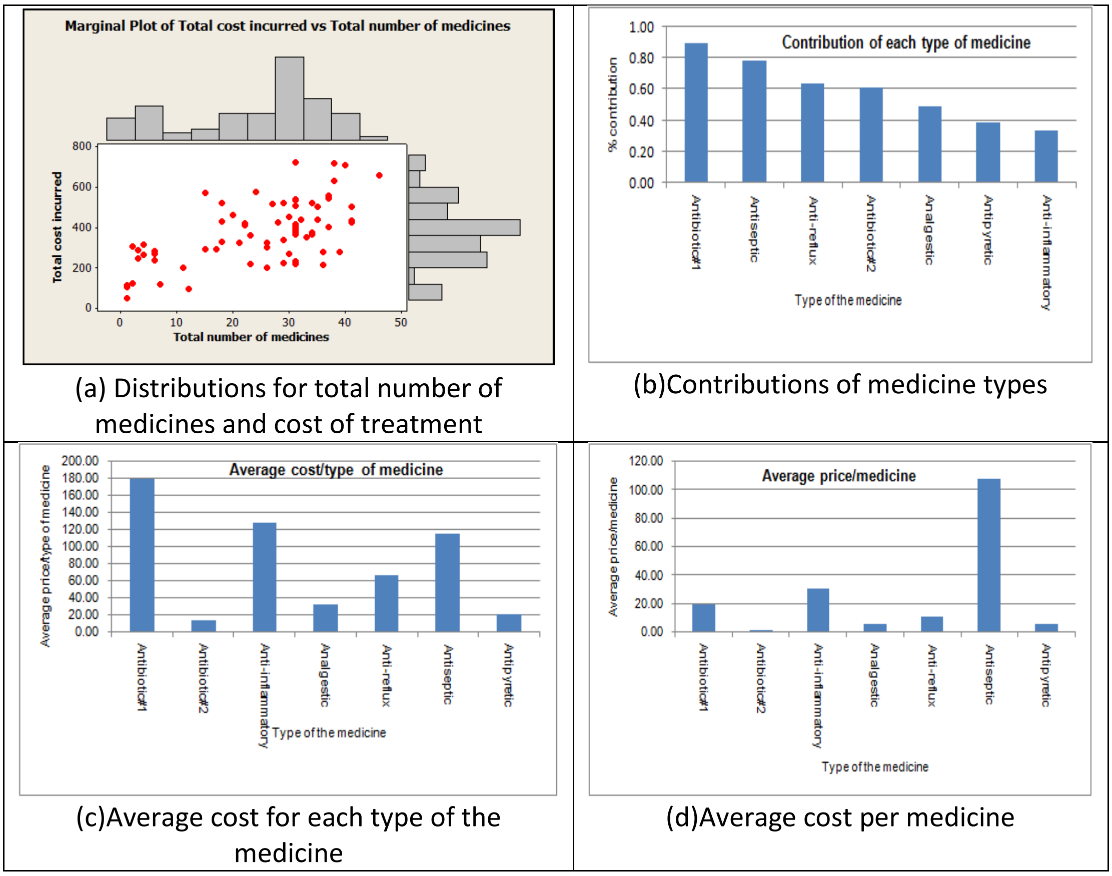
Case	Medicine#1	Medicine#2	Medicine#3	Medicine#4	Medicine#5	Medicine#6	Medicine#7
1.	Antibiotic#1	Antibiotic#2	Anti-inflammatory	Analgesic	Anti-reflux	Antiseptic	
2.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
3.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
4.	Antibiotic#1	Antibiotic#2	Anti-inflammatory	Analgesic	Anti-reflux	Antiseptic	
5.	Antibiotic#1	Antibiotic#2			Anti-reflux	Antiseptic	
6.	Antibiotic#1	Antibiotic#2			Anti-reflux	Antiseptic	Antipyretic
7.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
8.	Antibiotic#1	Antibiotic#2	Anti-inflammatory	Analgesic	Anti-reflux		
9.	Antibiotic#1				Anti-reflux	Antiseptic	Antipyretic
10.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
11.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
12.	Antibiotic#1	Antibiotic#2				Antiseptic	
13.	Antibiotic#1						
14.	Antibiotic#1	Antibiotic#2	Anti-inflammatory	Analgesic	Anti-reflux	Antiseptic	
15.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux		
16.	Antibiotic#1					Antiseptic	
17.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
18.	Antibiotic#1						
19.	Antibiotic#1			Analgesic	Anti-reflux	Antiseptic	
20.	Antibiotic#1		Anti-inflammatory				Antipyretic
21.	Antibiotic#1						Antipyretic
22.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	Antipyretic
23.	Antibiotic#1	Antibiotic#2					Antipyretic
24.			Anti-inflammatory				
25.	Antibiotic#1			Analgesic	Anti-reflux	Antiseptic	
26.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
27.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
28.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
29.	Antibiotic#1	Antibiotic#2		Analgesic		Antiseptic	
30.	Antibiotic#1	Antibiotic#2			Anti-reflux	Antiseptic	
31.	Antibiotic#1	Antibiotic#2	Anti-inflammatory				Antipyretic
32.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
33.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
34.	Antibiotic#1				Anti-reflux	Antiseptic	Antipyretic
35.						Antiseptic	
36.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
37.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
38.	Antibiotic#1		Anti-inflammatory	Analgesic		Antiseptic	
39.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
40.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
41.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
42.	Antibiotic#1		Anti-inflammatory	Analgesic	Anti-reflux	Antiseptic	
43.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
44.	Antibiotic#1	Antibiotic#2	Anti-inflammatory		Anti-reflux	Antiseptic	Antipyretic

Table 1. (*Continued***)**

Case	Medicine#1	Medicine#2	Medicine#3	Medicine#4	Medicine#5	Medicine#6	Medicine#7
45.						Antiseptic	Antipyretic
46.	Antibiotic#1				Anti-reflux	Antiseptic	Antipyretic

47.	Antibiotic#1		Anti-inflammatory				Antipyretic
48.	Antibiotic#1	Antibiotic#2			Anti-reflux	Antiseptic	
49.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
50.			Anti-inflammatory			Antiseptic	Antipyretic
51.	Antibiotic#1	Antibiotic#2	Anti-inflammatory				Antipyretic
52.	Antibiotic#1				Anti-reflux	Antiseptic	Antipyretic
53.	Antibiotic#1					Antiseptic	Antipyretic
54.	Antibiotic#1		Anti-inflammatory		Anti-reflux	Antiseptic	Antipyretic
55.	Antibiotic#1		Anti-inflammatory	Analgesic		Antiseptic	
56.	Antibiotic#1	Antibiotic#2			Anti-reflux	Antiseptic	Antipyretic
57.	Antibiotic#1	Antibiotic#2			Anti-reflux	Antiseptic	Antipyretic
58.	Antibiotic#1	Antibiotic#2				Antiseptic	Antipyretic
59.	Antibiotic#1	Antibiotic#2	Anti-inflammatory		Anti-reflux	Antiseptic	Antipyretic
60.	Antibiotic#1		Anti-inflammatory	Analgesic		Antiseptic	
61.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
62.	Antibiotic#1	Antibiotic#2		Analgesic		Antiseptic	
63.	Antibiotic#1		Anti-inflammatory	Analgesic	Anti-reflux	Antiseptic	
64.	Antibiotic#1	Antibiotic#2	Anti-inflammatory		Anti-reflux	Antiseptic	
65.			Anti-inflammatory			Antiseptic	
66.			Anti-inflammatory			Antiseptic	Antipyretic
67.	Antibiotic#1				Anti-reflux	Antiseptic	Antipyretic
68.	Antibiotic#1		Anti-inflammatory				Antipyretic
69.			Anti-inflammatory				Antipyretic
70.	Antibiotic#1	Antibiotic#2	Anti-inflammatory		Anti-reflux	Antisep1tic	Antipyretic
71.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux	Antiseptic	
72.	Antibiotic#1	Antibiotic#2		Analgesic			
73.	Antibiotic#1	Antibiotic#2	Anti-inflammatory		Anti-reflux		
74.						Antiseptic	Antipyretic
75.	Antibiotic#1	Antibiotic#2		Analgesic	Anti-reflux		Antipyretic

To have a detailed idea about the treatment of dental diseases, the original data is now analyzed. It can be noticed that average number of different medicine types, average number of medicines prescribed and average cost of treatment are respectively 4.24 (minimum = 1 and maximum = 6), 24.25 (minimum = 1 and maximum = 46) and INR 372.30 (minimum = INR 51.80 and maximum INR 721.10). It can also be interestingly noted that an adult patient usually required higher number of medicines with higher medication cost as compared to a child patient. The distributions for total number of medicines and cost of treatment in the form of histograms along with the respective data points are depicted in Figure 2(a). It can be revealed from Figure 2(b) that antibiotic#1 contributes maximally for the treatment of tooth pain and swelling problems, followed by antiseptic. Anti-inflammatory type of medicine plays minor role in treatment of those dental problems. In Figure 2(c), the average cost for each type of the prescribed medicine is presented and it reveals that antibiotic#1 is the most costly medicine type, followed by antiseptic type. Antibiotic#2 type of medicine is less costly. But, when the average cost per medicine is taken into consideration in Figure 2(d), it can be noticed that antiseptic is the costly medicine, followed by anti-inflammatory type. Antibiotic#2 has the minimum average cost.



(a) Distributions for total number of medicines and cost of treatment

(b)Contributions of medicine types

(c)Average cost for each type of the medicine

(d)Average cost per medicine

Figure 2. Results from the analyzed data

2. Development of association rules

In order to perform market basket analysis and development of the corresponding association rules, the medicines prescribed by the concerned dental physician are already shortlisted in Table 1, according to their classes for all the 75 treatment cases. This set of medicines is denoted as *I*, i.e. {antibiotic#1, antibiotic#2, anti-inflammatory, analgesic, anti-reflux, antiseptic, antipyretic}. Each treatment case is thus a subset of *I*. There are two principal methods of representing this type of data, i.e. transactional data format and tabular data format. The transactional data format requires two fields, i.e. an ID field and a content field with each record representing a single item only, as shown in Table 2. On the other hand, in tabular data format, each record represents a separate transaction with 0/1 flag fields and these indicate items, as exhibited in Table 3.

Table 2. Transactional data format for prescribed medicines

Transaction ID (Case ID)	Item
1.	Antibiobic#1
1.	Antibiobic#2
1.	Anti-inflammatory
1.	Analgesic
1.	Anti-reflux
1.	Antiseptic
2.	Antibiobic#1
2	Antibiobic#2
…	……..

Table 3. Tabular data format for prescribed medicines

Case	Antibiotic#1	Antibiotic#2	Anti-inflammatory	Analgesic	Anti-reflux	Antiseptic	Anti-pyretic
1.	1	1	1	1	1	1	0
2.	1	1	0	1	1	1	0
3.	1	1	0	1	1	1	0
4.	1	1	1	1	1	1	0
5.	1	1	0	0	1	1	0
6.	1	1	0	0	1	1	1
…	…	…	…	…	…	…	…

In the dataset, an item-set is a set of items contained in I and a k-item-set is an item-set containing k items. For example, {antibiotic#1} is an 1-item-set, {antibiotic#1, antibiotic#2} is a 2-item-set, {antibiotic#1, antibiotic#2, anti-inflammatory} is a 3-item-set data, and so on. The item-set frequency is the number of transactions that contain a particular item-set. Similarly, a frequent item-set is an item-set that occurs at least a certain minimum number of times, having item-set frequency ≥ Φ. For example, let us set Φ = 4. Thus, the item-sets that occur more than four k-item-sets are represented as F_k. The mining of association rules from a given dataset adopts the following two steps:

(a) Find all frequent item-sets, i.e. those item-sets with frequency ≥ Φ satisfying the minimum support.

(b) From the frequent item-sets, generate association rules satisfying the minimum support and confidence conditions.

For the development of association rules, *apriori* algorithm is mostly suited due to its various advantageous properties, like shrinkage of the search space, quick convergence etc. Tables 4 and 5 respectively depict 1-item-set and 2-item-set data from the original dataset of Table 1. As Φ = 4, an item-set is frequent if it occurs four or more number of times in D. In Table 4, as the individual occurrences of all the medicines meet or exceed Φ = 4, the frequent 1-item-set (F_1) can be developed as {antibiotic#1, antibiotic#2, anti-inflammatory, analgesic, anti-reflux, antiseptic, antipyretic}. Next, the frequent 2-item-sets (F_2) are developed. In general, to find F_k, the *apriori* algorithm first constructs a set of C_k of candidate k-item-sets by joining F_{k-1} with itself. It then prunes C_k using the *a priori* property. The item-sets in C_k that survive the pruning step finally form F_k. In this case, C_2 consists of all the combinations of medicines in Table 5. Since Φ = 4, F_2 would consist of all the possible combinations of the medicines, except {analgesic, anti-pyretic}. The frequent item-sets in F_2 are then utilized to generate C_3, the candidate 3-ietm-sets. To do so, join F_2 with itself, where item-sets are joined if they have the first (k – 1) items in common. For example, {antibiotic#1, antibiotic#2} and {antibiotic#1, anti-inflammatory} have the first (k – 1 = 1) (for k = 2) item in common, i.e. antibiotic#1. Thus, they can be joined into a new candidate item-set {antibiotic#1, antibiotic#2, anti-inflammatory}. In the similar direction, {antibiotic#2, analgesic} and {antibiotic#2, anti-reflux} have the first item, i.e. antibiotic#2 as common, which leads to the development of the candidate 3-item-set{antibiotic#2, analgesic, anti-reflux}. In this way, C_3 can be pruned using the *a priori* property. For each item-set s in C_3, (k – 1) subsets can be generated and examined. If any of these subsets is not frequent, s cannot be frequent and it can therefore be pruned. For example, let s = {antibiotic#1, antibiotic#2, anti-inflammatory}. The subsets of size (k – 1) = 2 are generated as follows: {antibiotic#1, antibiotic#2}, {antibiotic#1, anti-inflammatory} and {antibiotic#2, anti-inflammatory}. From Table 5, it can be noticed that these three 2-item-sets are frequent and thus, this set cannot be pruned. On the other hand, for s = {analgesic, antiseptic, anti-pyretic}, the subset {analgesic, anti-pyretic} has frequency 2 < 4 (Φ) and is not frequent. By the *a priori* property, {analgesic, antiseptic, anti-pyretic} is not frequent and is therefore pruned, not appearing in F_3. In this way, all the frequent item-sets need to examined and their occurrences are counted. The association rules are then generated from these frequent item-sets. This can be accomplished using the following two-step procedure, for each frequent item-set *s*:

a) At first, generate all subsets of *s*.
b) Consider *ss* as a non-empty subset of *s*.

Table 4. 1-item-set data

Type	Count	Type	Count	Type	Count
Antibiotic#1	67	Antibiotic#2	46	Anti-inflammatory	25
Type	Count	Type	Count	Type	Count
Analgesic	37	Anti-reflux	48	Antiseptic	59
Type	Count				
Anti-pyretic	29				

Consider the association rule *R*: $ss \Rightarrow (s - ss)$, where $(s - ss)$ indicates the set *s* without *ss*. Generate *R*, if *R* fulfils the minimum confidence requirement. Repeat this step for every subset *ss* of *s*. For example, consider *s* = {antibiotic#1, antibiotic#2, anti-inflammatory} from F_3. The proper subsets of *s* are {antibiotic#1}, {antibiotic#2}, {anti-inflammatory},{antibiotic#1, antibiotic#2}, {antibiotic#1, anti-inflammatory}and {antibiotic#2, anti-inflammatory}. For the first association rule, as shown in Table 6, consider *ss* = {antibiotic#1, antibiotic#2} so that $(s - ss)$ becomes {anti-inflammatory}. Thus, the corresponding rule is *R*: {antibiotic#1, antibiotic#2}$\Rightarrow${anti-inflammatory}. The support is the proportion of medical prescriptions in which both {antibiotic#1, antibiotic#2} and {anti-inflammatory} occur, which is 11 (or 14.67%) of the total 75 cases in *D*. To find out the confidence, the combination {antibiotic#1, antibiotic#2} occurs in 46 (or 61.33%) out of 75 cases, 11 of which also contain {anti-inflammatory}. Thus, based on the detailed analysis of the data in Table 1, the association rules from F_3 are generated with two antecedents. In the similar direction, the association rules with one antecedent are also developed in Table 7.

Table 5. 2-item-set data

Combination	Count	Combination	Count
{antibiotic#1, antibiotic#2}	46	{antibiotic#1, anti-inflammatory}	20
{antibiotic#1, analgesic}	37	{antibiotic#1, anti-reflux}	48
{antibiotic#1, antiseptic}	53	{antibiotic#1, anti-pyretic}	23
{antibiotic#2, anti-inflammatory}	11	{antibiotic#2, analgesic}	30
{antibiotic#2, anti-reflux}	38	{antibiotic#2, antiseptic}	38
{antibiotic#2, anti-pyretic}	14	{anti-inflammatory, analgesic}	9
{anti-inflammatory, anti-reflux}	11	{anti-inflammatory, antiseptic}	16
{anti-inflammatory, anti-pyretic}	11	{analgesic, anti-reflux}	31
{analgesic, antiseptic}	33	{analgesic, anti-pyretic}	2
{anti-reflux, antiseptic}	44	{anti-reflux, anti-pyretic}	14
{antiseptic, anti-pyretic}	19		

Based on the frequent 1-item-set of Table 4, it can be revealed that among the prescribed medicines for treatment of tooth pain and swelling, antibiotic#1 has the maximum number of occurrences, followed by antiseptic. The order of preference for the medicines is antibiotic#1→antiseptic→anti-reflux→antibiotic#2→anagesic→anti-pyretic→anti-inflammatory. Similarly, the 2-item-set data of Table 5 shows that the most preferred combination on medicines is {antibiotic#1, antiseptic}, followed by {antibiotic#1, anti-reflux}. On the other hand, there are least occurrences of {analgesic, anti-pyretic}combination in the list of prescriptions.

Table 6. Candidate association rules for medicines prescribed with two antecedents

If antecedent, then consequent	Support	Confidence	Support× Confidence
If antibiotic#1 and antibiotic#2, then anti-inflammatory	11/75	11/46	0.0351
If antibiotic#1 and antibiotic#2, then analgesic	30/75	30/46	0.2610
If antibiotic#1 and antibiotic#2, then anti-reflux	38/75	38/46	0.4185
If antibiotic#1 and antibiotic#2, then antiseptic	38/75	38/46	0.4185
If antibiotic#1 and antibiotic#2, then anti-pyretic	12/75	12/46	0.0417
If antibiotic#2 and anti-inflammatory, then analgesic	4/75	4/11	0.0194
If antibiotic#2 and anti-inflammatory, then anti-reflux	9/75	9/11	0.0982
If antibiotic#2 and anti-inflammatory, then antiseptic	8/75	8/11	0.0776
If antibiotic#2 and anti-inflammatory, then anti-pyretic	4/75	4/11	0.0776
If anti-inflammatory and analgesic, then anti-reflux	6/75	6/9	0.0194
If anti-inflammatory and analgesic, then antiseptic	7/75	7/9	0.0726
If anti-inflammatory and analgesic, then anti-pyretic	0/75	0/9	0
If analgesic and anti-reflux, then antiseptic	28/75	28/31	0.3372
If analgesic and anti-reflux, then anti-pyretic	1/75	1/31	0.0001
If anti-reflux and antiseptic, then anti-pyretic	13/75	13/44	0.0512

Table 7. Candidate association rules for medicines prescribed with one antecedent

If antecedent, then consequent	Support	Confidence	Support× Confidence
If antibiotic#1, then antibiotic#2	46/75 = 0.6133	46/67 = 0.6866	0.4211
If antibiotic#1, then anti-inflammatory	20/75 = 0.2667	20/67 = 0.2985	0.0796
If antibiotic#1, then analgesic	37/75 = 0.4933	37/67 = 0.5522	0.2724
If antibiotic#1, then anti-reflux	48/75 = 0.6400	48/67 = 0.7164	0.4585
If antibiotic#1, then antiseptic	53/75 = 0.7067	53/67 = 0.7910	0.5590
If antibiotic#1, then anti-pyretic	23/75 = 0.3067	23/67 = 0.3433	0.1053
If antibiotic#2, then anti-inflammatory	11/75 = 0.1467	11/46 = 0.2391	0.0351
If antibiotic#2, then analgesic	30/75 = 0.4000	30/46 = 0.6522	0.2610
If antibiotic#2, then anti-reflux	38/75 = 0.5067	38/46 = 0.8261	0.4186
If antibiotic#2, then antiseptic	38/75 = 0.5067	38/46 = 0.8261	0.4186
If antibiotic#2, then anti-pyretic	14/75 = 0.1867	14/46 = 0.3043	0.0568
If anti-inflammatory, then analgesic	9/75 = 0.1200	9/25 = 0.3600	0.0432
If anti-inflammatory, then anti-reflux	11/75 = 0.1467	11/25 =0.4400	0.0645
If anti-inflammatory, then antiseptic	16/75 = 0.2133	16/25 = 0.6400	0.1365
If anti-inflammatory, then anti-pyretic	11/75 = 0.1467	11/25 = 0.4400	0.0645
If analgesic, then anti-reflux	31/75 = 0.4133	31/37 = 0.8378	0.3463
If analgesic, then antiseptic	33/75 = 0.4400	33/37 = 0.8920	0.3924
If analgesic, then anti-pyretic	2/75 = 0.0267	2/37 = 0.0540	0.0001
If anti-reflux, then antiseptic	44/75 = 0.5867	44/48 = 0.9167	0.5378
If anti-reflux, then anti-pyretic	14/75 = 0.1867	14/48 = 0.2917	0.0544
If antiseptic, then anti-pyretic	19/75 = 0.2533	19/59 = 0.3220	0.0816

The mining of association rules generated with two antecedents, as shown in Table 6, shows that two rules, i.e. (If antibiotic#1 and antibiotic#2, then antiseptic) and (If antibiotic#1 and antibiotic#2, then anti-reflux) have the maximum support as well as confidence. Their strength is also high. The rule (If anti-inflammatory and analgesic, then anti-pyretic) has minimum support and confidence. From the prescriptions, it can be noticed that simultaneous occurrences of both the analgesic and anti-pyretic types of medicines are quite rare. The association rules with one antecedent, as provided in Table 7, exhibits maximum support and confidence for rule (If antibiotic#1, then antiseptic), followed by (If antibiotic#1, then anti-reflux). The rule (If analgesic, then anti-pyretic) has the minimum strength. Similarly, when the rules with three antecedents are developed, the rule (If antibiotic#1 and antibiotic#2 and antiseptic, then anti-reflux) appears with maximum strength. Thus, it can be concluded that for treatment of tooth pain and swelling, it would always be suggested to prescribe antibiotic#1 (Amoxycillin + Clavulanic Acid/Cefalexin/Ciprofloxacin), antibiotic#2 (Metronidazole), antiseptic (Chlorhexidine) and anti-reflux (Pantoprazole).

4. Conclusions

This paper aims in framing association rules for understanding the roles of different medicines prescribed for treatment of dental diseases, mainly tooth pain (odontalgia/dentalgia) and swelling of tooth (pericoronitis) based on 75 patient cases. Average number of different medicine types, average number of medicines prescribed and average cost of treatment are determined. The data reveals that an adult patient usually requires more medicines with extra medication cost as compared to a child patient. Antibiotic#1 contributes maximally to the treatment of tooth pain and swelling problems, followed by antiseptic. It is also the most costly medicine type, followed by antiseptic type. But, with respect to the average cost per medicine, antiseptic is the costly medicine, followed by anti-inflammatory type. Antibiotic#2 has the minimum average cost. Based on 2-item dataset, {antibiotic#1, antiseptic} is the most preferred combination on medicines, followed by {antibiotic#1, anti-reflux}. Among the association rules, the rule (If antibiotic#1 and antibiotic#2 and antiseptic, then anti-reflux) appears with the maximum strength. Thus, it is recommended to have antibiotic#1 (Amoxycillin + Clavulanic Acid/Cefalexin/Ciprofloxacin), antibiotic#2 (Metronidazole), antiseptic (Chlorhexidine) and anti-reflux (Pantoprazole) for treatment of tooth pain and swelling problems. These types of association rules can also be generated for treatment of other diseases to have an idea about the contribution of each type of medicine in curing a particular disease.

References

Adewole, K. S., Akintola, A. G., Ajiboye, A. R., & Abdulsalam, K. S. (2014). Frequent pattern and association rule mining from inventory database using apriori algorithm. African Journal of Computing & ICT, 7(3), 35-41.

Agarwal, R., & Mittal, M. (2019). Inventory classification using multi-level association rule mining. International Journal of Decision Support System Technology, 11(2), 1-9.

Arul Valan, J., & Baburaj, E. (2020). Inventory control in healthcare supply chain management using apriori and gravitational search algorithms. International Journal of Logistics Systems and Management, 35(4), 511-525.

Bala P.K. (2009). Data mining for retail inventory management. In: Ao, S.I., Gelman, L. (eds) Advances in Electrical Engineering and Computational Science, Springer, 39, 587-598.

Bala, P. K., Sural, S., & Banerjee, R. N. (2010). Association rule for purchase dependence in multi-item inventory. Production Planning & Control, 21(3), 274-285.

Gupta, D., & Chauhan, A. S. (2013). Mining association rules from infrequent itemsets: A survey. International Journal of Innovative Research in Science, Engineering and Technology, 2(10), 5801-5808.

Han, J., Kamber, M., & Pei, J. (2012). Data Mining Concepts and Techniques. Elsevier Inc., USA.

Jaiswal, V., & Agarwal, J. (2012). The evolution of the association rules. International Journal of Modeling and Optimization, 2(6), 726-729.

Kaur, G. (2014). Association rule mining: A survey. International Journal of Computer Science and Information Technologies, 5(2), 2320-2324.

Kotsiantis, S., & Kanellopoulos, D. (2006). Association rules mining: A recent overview. GESTS International Transactions on Computer Science and Engineering, 32(1), 71-82.

Kulkarni, A. R., & Mundhe, S. D. (2017). Data mining technique: An implementation of association rule mining in healthcare. International Advanced Research Journal in Science, Engineering and Technology, 4(7), 62-65.

Kusiak, A., Kern, J. A., Kernstine, K. H., & Tseng, B. T. L. (2000). Autonomous decision-making: A data mining approach. IEEE Transactions on Information Technology in Biomedicine, 4(4), 274-284.

Lakshmi K. S., & Vadivu, G. (2017). Extracting association rules from medical health records using multi-criteria decision analysis. Procedia Computer Science, 115, 290-295.

Mandave, P., Mane, M., & Patil, S. (2013). Data mining using association rule based on APRIORI algorithm and improved approach with illustration. International Journal of Latest Trends in Engineering and Technology, 3(2), 107-113.

Meenakshi, R. (2014). A review on association rule mining. International Journal of Advance Research in Science and Engineering, 3(5), 299-303.

Mukherjee, S., Gupta, P., & Musau, F. (2018). Integrating application with algorithms of association rule used in descriptive data modelling, through which data mining can be implemented for future prediction. International Journal of Applied Engineering Research, 13(17), 13272-13281.

Sadoyan, H., Zakarian, A., & Mohanty, P. (2006). Data mining algorithm for manufacturing process control. International Journal of Advanced Manufacturing Technology, 28, 342-350.

Shaukat, K., Zaheer, S., & Nawaz, I. (2015). Association rule mining: An application perspective. International Journal of Computer Science and Innovation, 1(1), 29-38.

Thakur, R. K., & Shah, K. (2012). An efficient approach for association rule mining. International Journal of Scientific & Engineering Research, 3(5), 1-4.

Wang, K. (2007). Applying data mining to manufacturing: the nature and implications. Journal of Intelligent Manufacturing, 18, 487-495.