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Exploring Bangladesh's Pharmaceutical Purchase Trends: Perspectives from Periodicity Analysis and Association Rule Mining on Retail Transactions

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ABSTRACT

This investigation explores consumer pharmaceutical purchasing behaviors using an extensive data set from Bangladeshi medical supply vendors. Over 29 months, we analyzed 30,947 transactions involving 3,016 unique items. By employing association rule mining, we identified common product purchase combinations and recurrent patterns reflecting customer behavior and market dynamics. We thoroughly analyzed association rules and periodic items to understand how varying support and confidence levels impact rule formation and product recognition. As support levels increase from 0.5% to 5%, fewer but more significant rules emerge, with a fixed support level at 0.75% and confidence at 10%, demonstrating a trade-off between rule quantity and significance. A category-specific analysis shows that higher support levels lead to fewer rules, indicating a greater acceptance of specific products. Through customized algorithms, this study uncovers patterns and trends in pharmaceutical purchases, providing insights that could influence marketing tactics, policy decisions, and stock management in the healthcare retail industry. These results offer a comprehensive understanding of consumer behavior and market demands in a vital sector of Bangladesh's economy.

Keywords: Association rule; Data mining; Pharmaceuticals; Periodicity; Medicine association; Transactions; Duplicate transaction; Confidence.

1. Introduction

In the dynamic realm of pharmaceuticals, where every product plays a pivotal role in healthcare, understanding consumer behavior and purchase patterns is crucial. Association rule mining is a powerful method for uncovering hidden relationships within datasets, widely used across various industries, including pharmaceuticals. This technique helps identify frequently co-purchased pharmaceutical products, highlighting prevalent health concerns within specific demographics. With this knowledge, pharmaceutical businesses can tailor their sales and marketing strategies more effectively. For instance, if products X and Y are often bought together, sales plans can be designed to inform customers about complementary products, enhancing overall customer satisfaction.

Our study leverages the power of association rule mining by meticulously examining a dataset from a reputable pharmaceutical store. This dataset comprises 30,947 authentic daily transaction records from a renowned medical outlet in Bangladesh. Our rigorous data analysis, which includes assessing transaction delicacy ratios, category diversity, and periodicity, empowers medical retailers to make informed decisions. This enables swift adaptations to evolving consumer preferences, ensures timely stocking of relevant merchandise, and enhances the overall shopping experience for customers.

A critical aspect of our analysis is investigating the recurrence of specific purchase patterns within the diverse array of products available in a medical store. The ratio between total and duplicate categories indicates the frequency of repeated purchase combinations, offering valuable insights into consumer preferences, trends, and potential product relationships. Analyzing purchasing patterns and correlations across different time periods, or periodicity, is essential to understand the dynamic nature of consumer behavior. The structure of our paper is organized as follows: the introduction provides an overview of association rule mining and outlines our research motivations and objectives. The subsequent section reviews relevant literature pertaining to our research objectives. Following this, the methodology section details our datasets, data preprocessing techniques, and analytical methodologies. The results and discussion section present our experimental findings and their implications. Finally, the conclusion section encapsulates the key insights from our study and offers avenues for future research.

1.1. Study Objectives

(i) To assess pharmaceutical product buying trends in Bangladesh; (ii) To analyze the consequences of varying support and confidence for the association rules and product transaction's pattern; (iii) To discover pharmaceuticals buying trends and patterns based on specific categories of pharmaceutical; (iv) Assess Transaction Delicacy Ratios and Category Diversity; and (v) Inform Sales and Marketing Strategies.

2. Related Works

An experimental study was conducted on rabbits. Several studies have explored the application of association rule mining in healthcare and retail sectors, contributing valuable insights into the field. Doddi et al. [1] examined medication procedures and patient diagnosis reports using randomized samples to uncover association rules, revealing relationships between medical treatments and patient conditions. Rashid et al. [2] focused on optimizing disease co-occurrences in patient repositories, developing a predictive system integrated with OLTP data to highlight disease interconnections within patient populations. Khedr et al. [3] utilized association mining on a distributed medical database to create a predictive model for heart disease, addressing patient data privacy concerns while providing insights into disease prediction.

In the realm of data privacy, Darwish et al. [4] proposed a data sanitization method to protect patient privacy in data mining procedures, demonstrating its effectiveness compared to existing methods. Nadeak & Ali [5] combined artificial intelligence techniques with the Apriori method to analyze medication sales, presenting association rules that offered insights into consumer behavior and purchasing patterns in pharmaceutical retail. Khader et al. [6] automated pharmacy systems using the FP-Growth method to explore associations in prescribed pharmaceutical data, aiming to optimize pharmacy operations and enhance patient care. Utami & Jananto [7] investigated client purchasing behavior in medical shops using the Apriori algorithm, providing insights for retail strategy optimization by analyzing customer demographics and purchase preferences. Islam et al. [11] analyzed a large transactional dataset from a mega-supermarket, segmenting the dataset based on time to understand consumer behavior dynamics.

Dongre et al. [8] examined data mining algorithms using simulated datasets, demonstrating the application of the Apriori algorithm and contributing to a deeper understanding of algorithmic techniques. Changchien & Lu [10] focused on support-based data mining of association rules, utilizing neural network clustering and rough set theory to provide insights into data analysis techniques.

Shah [12] proposed a modified Apriori algorithm to discover association rules more efficiently, improving the performance of association rule mining in large datasets. Rana & Mondal [13] analyzed real supermarket transaction data to identify association rules and seasonal product buying patterns, offering insights into consumer behavior in retail environments.

Widely used data mining algorithms for regular item extraction and association rule generation include Apriori [13], FP-Growth [14], Eclat [15], and K-Apriori [16]. The FP-Growth algorithm, in particular, has been instrumental in uncovering seasonal association rules [12]. However, consumer preferences vary significantly throughout the day, leading to fluctuations in product demand and affecting the generation of association rules, resulting in higher periodicity for certain items. The Apriori algorithm, despite being renowned for frequent pattern mining, has drawbacks such as continuous dataset scanning and generating numerous candidate item sets, which can reduce efficiency [17,18].

Market basket analysis includes various aspects, including fuzzy association rules mining [19], periodic-frequent pattern mining [20], positive and negative association mining [21], generalized association rules, spatial rules [22], quantitative rules, interesting association rules, inter-transaction rules, and temporal association rules [23,24]. Studies focusing on product promotion and buying patterns [25] further enrich this field, employing traditional data mining and association rule mining algorithms.

3. Research Methodology

Our research methodology consists of a detailed plan that includes gathering, handling, analyzing, and interpreting sales data. This methodology section provides a full explanation of the exact procedures and methods used at each stage of this study.

3.1. Data collection

The first step of our main task was gathering the data. The data used in this study was collected from reliable medical supply vendors in Bangladesh. These retailers included a wide variety of pharmacies, both standalone and affiliated with bigger chains, as well as inpatient clinical products. Our dataset contains 30,947 transactions by medicine name and also generic name with 3,016 unique medicines and 545 unique generic medicines.

Table 1. Product types in datasets

Sl. No.	Product types
1.	Medicines
2.	Clinical
3.	Surgical

These sources were chosen because they provided thorough sales statistics and represented a wide range of consumer purchase behaviors in the pharmaceutical industry. The dataset's more than two-year span of transaction records provides an adequate chronological structure to support the research. Each of the records in the collection contains crucial information such as the product name, product ID, quantity sold, date and time of the transaction, and price. The brand name and generic name of the products are also maintained separately.

3.2. Data pre-processing

At this stage, several important steps are completed to enhance data quality, preserve reliability, and make the dataset ready for use with mining algorithms. The process takes some subsection as follows:

● **Data Cleaning:** Records with missing fields or values were looked through. Depending on the specifics of the case, values that weren't available were either eliminated from the dataset or imputed using statistical procedures to preserve data integrity. To avoid distorting the findings, sales activities that showed extreme numbers were found and eliminated. These transactions were probably the result of data entry errors or atypical purchase behavior.

● **Data Transforming:** This process includes two steps, such as data normalization and data aggregation. To maintain consistency between transactions, the price attribute of products is normalized to account for variances in insertion. After that, an essential step of association mining, 'aggregation', is adapted for combining all purchased products in a single transaction into one record.

● **Data Segmentation:** Relevant criteria, including product brand categories and product main or generic categories, were used to segment the dataset. This stage made it possible to conduct a more focused analysis, which made it easier to find trends unique to certain market sectors or customer demographics.

The dataset was carefully cleaned, transformed, encoded, and segmented to make it more streamlined and organized so that association rule mining could be performed on it.

3.3. Association rules mining working procedure

Shedding light on the pharmaceutical product buying nature in Bangladesh, we have paid close attention to the daily transactions of our working datasets. The task at hand was to gain insight into the complexities of pharmaceutical sales in a nation facing various healthcare issues, rather than just being an academic endeavor. Table 2 outlines the comprehensive steps undertaken in our methodology.

Table 2. Working Steps

Steps	**Description**
Start	The initial point is where we want to find some new work.
Data Collection	Our investigation was centered on finding trends in the simultaneous purchase of pharmaceuticals. We tried to address two important queries: First, are certain pharmaceuticals often purchased together? Secondly, are these buying habits consistent with any underlying pattern? With the assurance that we won't sell the information or engage in any form of harassment, we gather medical shop data as an SQL file. Data on medication transactions was gathered throughout 29 months, from May 2021 to September 2023.
SQL File Preparation	Initially, we set up the SQL file on the local XAMPP server. After that, we export the data into an Excel file using the following query: "SELECT sales_details_time, sales_details_sales_id, product_name, main_category_name from product, sales_details, main_category where sales_details_product=product_id and product_main_category=main_category_code". The name of the above Excel file is main_categories.csv.

Excel file preparation	We prepare several Excel files from main_categories.csv, such as: **i. Product_Categories_row.csv:** In this file, the selling transactions are in rows where the column value is the category or generic name of each product. Here, some rows may have duplicate column values as per what the user (patient) needs or what the doctor has prescribed. Using this file, we can find a scenario in which a patient purchases a product in the same category. **ii. Product_without_Duplicacy_Category_Row.csv:** This is the updated version of the previous file (Product_Categories_row.csv), where duplicate columns in a row are emitted. This file is used to find the periodicity of each category for acquiring the periodic frequent category. As well as to find out the association rules among the categories. **iii. Product_Name_Row.csv:** The scenario of medicine buying as a medicine name is shown in this file. This file is used to find the periodicity of each medicine for acquiring periodic frequent medicine. As well as to find association rules among medicines.
Analysis of Product categories.	This step finds the periodicity of the duplicate ratio, the mode value, as well as the maximum periodicity.
Find periodicity	Here, we get the periodic value of each category from a product without duplicacy category rows. And also periodic values for each medicine from the product_name_row file.
Finding Association Rules	The output of association rules for both categories (generic products) and pharmaceutical brand names.
Analysis	Output analysis.
End	The end of work.

3.4. Working algorithms

Our primary focus was on discovering association rules and identifying periodic frequent patterns for medicines and their categories. We generated frequent item-sets from transactional databases using tree-based FP-growth concepts. However, we encountered challenges when multiple products from the same category were purchased in a single transaction. To address this issue, we developed an algorithm to eliminate duplicate categories, as detailed in Algorithm 1 and Algorithm 2. Additionally, using this algorithm, we calculated interesting metrics such as the ratio of purchases involving duplicate category products, the periodicity of these duplicate categories, and their mode.

So, through the careful use of sophisticated algorithms to analysis 29 months' worth of transaction data, we were able to determine not only which pharmaceutical product combinations were most commonly purchased together, but also the patterns of periodicity and persistence in these purchases.

Algorithm 1. Part 1: Periodicity and mode of Duplicate Categories()

Input: Pro._without_Dup._Cat._Row.csv as an input file
Output: Periodicity of Duplicate Categories and Mode

```
duplicateItems[2499] ← empty
duplicate_count ← 0
duplicate_tran ← 0
tran_count ← 0
duplicate_tran_ar[1690] ← empty
try:
    br ← BufferedReader(newFileReader("Pro._Cat_Row.csv"))
    fileWriter ← FileWriter("Pro._Without_Dup._Cat_Row.csv")
    while (line != br.readLine()) do
        transcetion_count++
        arrayWithDuplicate[] ← line.split(", ")
        uniqueE ← newArrayListofstrings
        duplicateE ← newArrayListofstrings
        set ← newHashSetofstrings
        for each element in array With Duplicates do
            if element is not in set then
                set ← element
                uniqueE ← element
            else
                duplicateE ← element
        arrayWithoutDup[] ← uniqueEtoArray(newString[0])
        arrayDup[] ← duplicateE.toArray(newString[0])
        if arrayDup.length > 0 then
            duplicate_tran_ar[duplicate_tran + +] ← tran_count
        for i = 0; i < arrayDup.length − 1 do
            duplicateItems[duplicate count + +] ← arrayDup[i]
        for i = 0; i < arrayWithoutDup.length − 1 do
            fiileWriter.append(arrayWithoutDup[i] + ", ")
        fileWriter.append("newline")
    fileWriter.flush()
    fileWriter.close()
    br.close()
    catch IndexOutOfBoundsException:
        printstacktraceof the exception
```

Algorithm 2. Second Part of 1st Algorithm

```
total ← 0
gap[duplicate_tran_ar.length] ← empty
```

```
for i = 0; i < duplicate_tran_ar.length − 2 do
    sub ← duplicate_tran_ar [i + 1] – duplicate_tran_ar[i]
    total ← total + sub
    gap[i] ← sub
    if sub > period then
        duplicate_tran_ar [duplicate_tran + +] ← tran_count
print "Maximumperiodicity : " + period
Arrays.sort(gap)
mode ← 0
b_count ← 0
←
for i = 0; i < duplicate_tran_ar.length − 1 do
    if i ≠ 0 then
        if gap[i] ≠ gap[i − 1] then
            b_count ← 0
            for j = 0; j < duplicate_tran_ar.length − 1 do
                if gap[i] == gap[j] then
                    b_count + +
            if b_count > mode then
                mode ← b_count
                period ← gap[i]
    else
        b_count ← 0
        for j = 0; j < duplicate_tran_ar.length − 1 do
            if gap[i] == gap[j] then
                b_count + +
            else
                break
        mode ← b_count
        period ← gap[i]
    print "Mode : " + mode
    return;
```

4. Result and Discussion

In order to identify the duplicate categories sold in a transaction, we begin our research activities with dataset analysis. Table 3 presents the numerical data related to our study dataset.

Table 3. Details about redundant categories and datasets

Terms	Values
Transactions	30947
Products	3016
Category	545
Duplicate transaction	1690
Duplicate category	138
Duplicate transaction vs. duplicate category (%)	25.3
Periodicity of duplicate categories	130

As a consequence, there are 30947 transcriptions in the datasets, which encompass 545 distinct categories (generics). On the other hand, in 1690, patients did not purchase multiple identical generic medications. Evidently, there are 138 categories with multiple duplicates. At least one patient purchases duplicate categories of medication for every 130 transactions, according to the Maximum Periodicity of Duplicate Categories Transactions (130). The greatest number of gap-less and mode segments, or 157, is found when we compute the mode of gap between two duplicate transcriptions. Based on the input parameters of our research algorithm, we optimized the result of the category (the generic name of the pharmaceutical product) by making the confidence static with variable support values, the support static with variable confidence values, and variable periodicity values as in Table 4.

Table 4. Analysis of Association rules and Periodic items for categories (generic product)

Fixed confidence = 10%		Fixed support = 0.75%		Periodic Frequent Products	
Support (%)	**Rules for categories**	**Confidence (%)**	**Rules for categories**	**Threshold Periodic value**	**Frequent product for categories**
0.5	1127	1	1585	100	2
0.75	244	5	589	200	8
1	123	10	244	500	27
1.5	48	15	207	700	50
2	28	20	127	900	64
3	17	25	111	1000	68
4	10	30	101	1500	108
5	5	50	87	2000	136

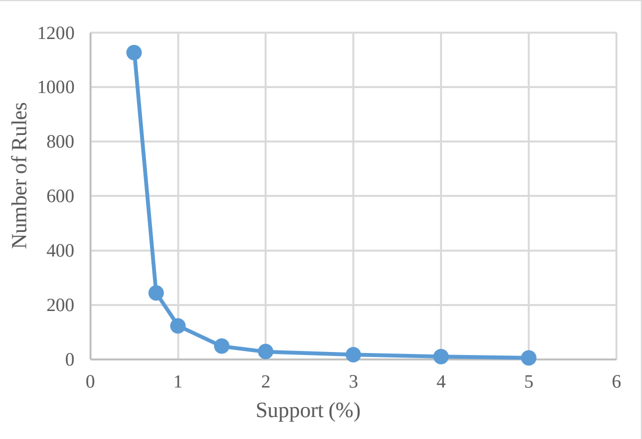
A detailed analysis of association rules and the identification of products in various generic product categories that are periodically frequented are presented in Table 4. A fixed support level of 0.75% and a predefined confidence level of 10% are applied in the analysis. The purpose of the table is to demonstrate how varying the support threshold influences the number of trustworthy association rules, the level of trust that can be placed in these rules, and the capacity to recognize commodities regularly used under various threshold periodic values. It is evident that when the support level increases from 0.5% to 5%, there are fewer association rules. This suggests that, even though fewer rules might be generated at higher support levels, they might be more important or pertinent. Also, the increased confidence in the regulations correlates with the support threshold growth. At the lowest degree of support (0.5%), confidence is just 1%, and at the highest level (5%), it rises to 50%.

Table 5 presents the results of the study on periodic item identification and association rules for a specific brand product, with a 10% confidence level and a 0.5% support threshold. The table is broken down into six sections that contain data on threshold periodic values, the number of frequently identified products for the brand product under different support conditions, the number of rules developed for the brand product, and the confidence percentage associated with these rules. The table shows that there is a discernible drop in the number of rules generated as the support percentage rises from 0.1% to 1%, from 2359 rules at 0.1% support to only 33 rules at 1% support. This drop suggests increasing levels of acceptance with more granular regulations. 5 to 50% confidence ranges for these rules indicate varying degrees of reliability in the anticipated brand-item correlations. With 2000 representing the highest support level (1%), and 500 representing the lowest support level (0.1%), the table shows a growing threshold periodic value. This increase is consistent with the expanding periodicity of item occurrence with increased support and suggests a wider interval of product occurrences with tighter support requirements.

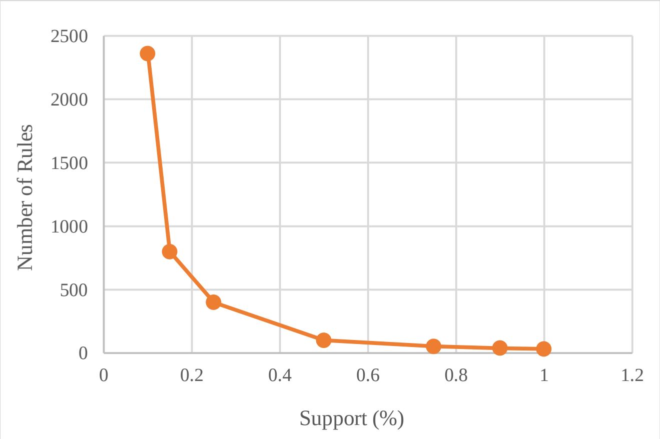
Table 5. Analysis of Association rules and Periodic items for Brand Product

Fixed confidence = 10%		Fixed support = 0.5%		Random periodicity	
Support (%)	**Rules for brand product**	**Confidence (%)**	**Rules for brand product**	**Threshold Periodic value**	**Frequent product for brand product**
0.1	2359	5	193	500	5
0.15	799	10	145	700	16
0.25	400	15	141	900	23
0.5	100	20	137	1000	33
0.75	52	30	136	1200	43
0.9	39	40	134	1500	59
1	33	125	125	2000	105

Figure 1 depicts the association rules under a fixed confidence variable threshold value of support. Consequently, Figures 1(a) and 1(b) illustrate categories and brand names accordingly. It is observed that more frequent categories are obscured by patient data. As a result, at the 1% threshold value in Figure 1(b), which represents the final point on the graph, the least number of association rules are generated. Conversely, the final point in Figure 1(a) corresponds to a 5% threshold value.



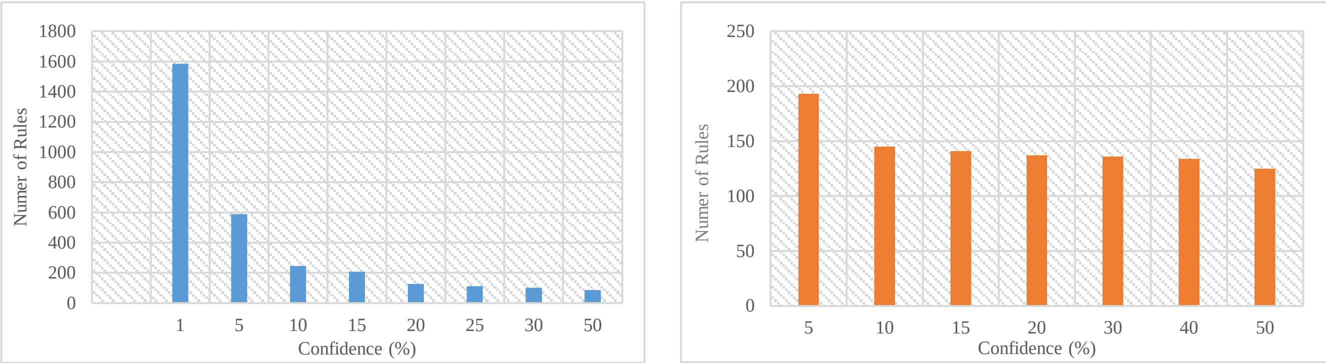
(a)



(b)

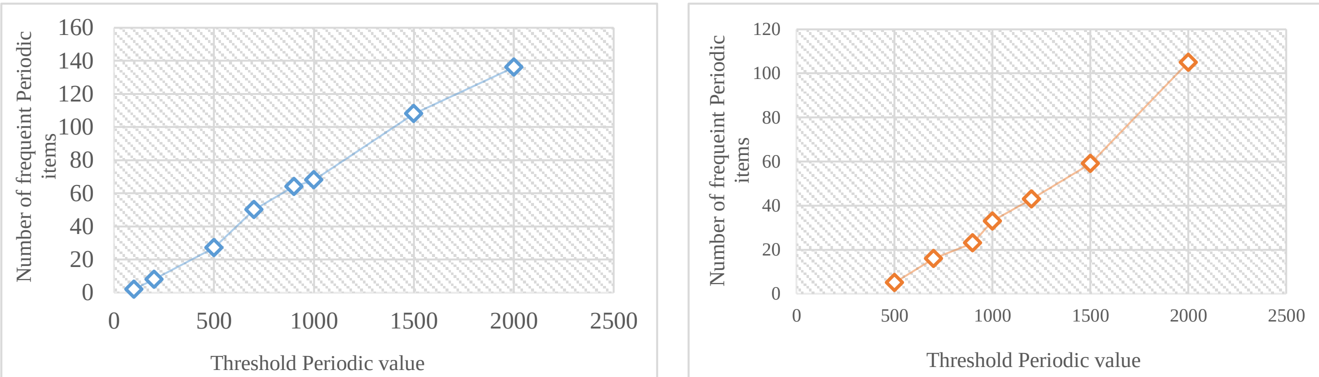
Figure 1. Association Rules when Fixed confidence = 10% for (a) medicine in categories, and (b) medicine in brand name

Figure 2 illustrates the association rules concerning medicine categorized by both product categories and brand names, with fixed support values and variable confidence values represented in subfigures (a) and (b) respectively. Both subfigures elucidate the influence of increasing confidence values on generated association rules. Notably, Figure 2(a) displays a notable abundance of association rules across various confidence threshold values, indicating a significant impact of confidence level adjustments on the rule generation.



(a) (b)

Figure 2. Association Rules when Fixed support = 0.75% for (a) medicine in categories, and (b) medicine in brand name



(a) (b)

Figure 3. Period Frequent pattern for (a) medicine in categories, and (b) medicine in brand name

The graphical representation in Figure 3 elucidates the impact of periodic threshold values. In Figure 3(a), we observe periodic frequent patterns for medicine, classified by product categories. Notably, the initial significant pattern emerges at a threshold periodic value of 100, showcasing the evolution of these patterns as the threshold value changes. Similarly, Figure 3(b) showcases periodic frequent patterns for medicine categorized by brand names, with the first notable pattern appearing at a threshold periodic value of 500. Upon comparing both figures, it becomes evident that frequent patterns are more distinctly visible for categories compared to brand names.

5. Conclusion

We have unearthed significant insights into consumer purchasing patterns and recurring themes by applying sophisticated association rule mining algorithms and diligent data preparation. We employed a thorough process of data cleansing, transformation, and segmentation to prepare the dataset for analysis. This process safeguarded the integrity of the data and facilitated the identification of noteworthy trends. Through the application of advanced algorithms, we were able to determine which pharmaceuticals were regularly purchased together and understand the consistency and regularity of these buying patterns. Significant findings indicated variations in consumer behavior and strong relationships between brand names and generic product categories. The analysis revealed that a substantial portion of transactions involved multiple purchases of comparable generic medications, indicating the recurrent nature of these purchases. Further evidence of stronger associations at higher support levels was provided by the observation that although the number of association rules decreased as the support threshold increased, their relevance and confidence levels grew.

Overall, this study advances our understanding of the dynamics of pharmaceutical sales in Bangladesh by providing a methodological framework that can be applied to similar research in other fields or industries.

Future research could extend these findings by investigating the influence of external factors such as seasonal trends, economic variations, and geographic disparities on pharmaceutical purchasing patterns. Additionally, incorporating multilevel association rule analysis techniques could provide deeper insights into the purchasing trends of medicines across different zones or areas. This approach would allow for a more nuanced understanding of how various external conditions impact the demand for pharmaceutical products, potentially leading to more targeted and effective marketing and distribution strategies. Furthermore, the inclusion of additional variables, such as demographic factors or health policy changes, could enhance the predictive accuracy of these models and provide a more comprehensive view of consumer behavior in the pharmaceutical sector.

Declarations

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Competing Interests Statement

The authors declare no competing financial, professional, or personal interests.

Consent for publication

The authors declare that they consented to the publication of this study.

Authors' contributions

All the authors took part in literature review, analysis and manuscript writing equally.

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References

[1] Doddi, S., Marathe, A., Ravi, S.S., & Torney, D.C. (2001). Discovery of association rules in medical data. Medical Informatics and the Internet in Medicine, 26(1): 25–33. doi: 10.1080/14639230117529.

[2] Rashid, M.A., Hoque, M.T., & Sattar, A. (2014). Association Rules Mining Based Clinical Observations. ArXiv./abs/1401.2571.

[3] Khedr, A.M., Aghbari, Z.A., Ali, A.A., & Eljamil, M. (2021). An Efficient Association Rule Mining from Distributed Medical Databases for Predicting Heart Diseases. IEEE Access, 9: 15320–15333. doi: 10.1109/access.2021.3052799.

[4] Darwish, S.M., Essa, R.M., Osman, M.A., & Ismail, A.A. (2022). Privacy Preserving Data Mining Framework for Negative Association Rules: An Application to Healthcare Informatics. IEEE Access, 10: 76268–76280. doi: 10.1109/access.2022.3192447.

[5] Nadek, Irianto, S., & Ali, Y. (2021). Analysis of Data Mining Associations on Drug Sales at Pharmacies with APRIORI Techniques. IJISTECH, 5(1): 38–44.

[6] Khader, N., Lashier, A., & Yoon S.W. (2016). Pharmacy robotic dispensing and planogram analysis using association rule mining with prescription data. Expert Systems with Applications, 57: 296–310. doi: 10.1016/j.eswa.2016.02.045.

[7] Utami, F.P., & Jananto, A. (2023). Implementation of the Association Rule Method using Apriori Algorithm to Recognize the Purchase Pattern of Pharmacy Drugs "XYZ". Journal of Computer Engineering, System and Science, 8(1). doi: 10.24114/cess.v8i1.40377.

[8] Dongre, J., Prajapati, G.L., & Tokekar, S.V. (2014). The role of Apriori algorithm for finding the association rules in Data mining. International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), Ghaziabad, India, Pages 657–660. doi: 10.1109/icicict.2014.6781357.

[9] Houtsma, M., & Swami, A. (1995). Set-oriented mining for association rules in relational databases. Proceedings of the Eleventh International Conference on Data Engineering, Taipei, Taiwan, Pages 25–33. doi: 10.1109/icde.1995.380413.

[10] Changchien, S.W., & Lu, T.C. (2001). Mining association rules procedure to support the on-line recommendation by customers and products fragmentation. Expert Systems with Applications, 20(4): 325–335. doi: 10.1016/s0957-4174(01)00017-3.

[11] Islam, M.R., Rahman, M.S., & Nayeem, M.J. (2023). Association Rules Mining for a Specific Time Period in a Day in Large Transactional Database. International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD), Pages 402–406. doi: 10.1109/icict4sd59951.2023.10303523.

[12] Shah, A. (2016). Association rule mining with modified apriori algorithm using top-down approach. 2nd International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), Bangalore, India, Pages 747–752. doi: 10.1109/icatcct.2016.7912099.

[13] Rana, S., & Mondal, M.N.I. (2021). A Seasonal and Multilevel Association Based Approach for Market Basket Analysis in Retail Supermarket. European Journal of Information Technologies and Computer Science, 1(4): 9–15. doi: 10.24018/compute.2021.1.4.31.

[14] Agrawal, R., Imieliński, T., & Swami, A. (1993). Mining association rules between sets of items in large databases. Proceedings of the ACM SIGMOD International Conference on Management of data, Pages 207–216.

[15] Nasyuha, A.H., Jama, J., Abdullah, R., Syahra, Y., Azhar, Z., Hutagalung, J., & Hasugian, B.S. (2021). Frequent pattern growth algorithm for maximizing display items. Telkomnika, 19(2): 390–396.

[16] Ma, Z., Yang, J., Zhang, T., & Liu, F. (2016). An improved eclat algorithm for mining association rules based on increased search strategy. International Journal of Database Theory and Application, 9(5): 251–266.

[17] Annie, L.C.M., & Kumar, A.D. (2012). Market basket analysis for a supermarket based on frequent itemset mining. International Journal of Computer Science Issues, 9(5): 257–64.

[18] Chen, Y.L., Tang, K., Shen, R.J., & Hu, Y.H. (2005). Market basket analysis in a multiple store environment. Decision Support Systems, 40(2): 339–354.

[19] Khan, M.A., Solaiman, K.M., & Pritom, T.H. (2017). Market basket Analysis for improving the effectiveness of marketing and sales using Apriori, FP Growth and Eclat Algorithm. PhD Dissertation, BRAC University, Bangladesh.

[20] Saputra, J., Rahayu, S., & Hariguna, T. (2023). Market Basket Analysis Using FPGrowth Algorithm to Design Marketing Strategy by Determining Consumer Purchasing Patterns. Journal of Applied Data Sciences, 4(1): 38–49. doi: 10.47738/jads.v4i1.83.

[21] Zheng, H., He, J., Huang, G., Zhang, Y., & Wang, H. (2019). Dynamic optimization based fuzzy association rule mining method. International Journal of Machine Learning and Cybernetics, 10(8): 2187–2198.

[22] Kiran, R.U., Kitsuregawa, M., & Reddy, P.K. (2016). Efficient discovery of periodic-frequent patterns in very large databases. Journal of Systems & Software, 112: 110–121.

[23] Wu, X., Zhang, C., & Zhang, S. (2004). Efficient mining of both positive and negative association rules. ACM Trans Information Systems, 22(3): 381–405.

[24] Shi, W., Zhang, A., & Webb, G.I. (2018). Mining significant crisp-fuzzy spatial association rules. International Journal of Geographical Information Science, 32(6): 1247–1270.

[25] Aljawarneh, S.A., Radhakrishna, V., & Cheruvu, A. (2020). VRKSHA: a novel tree structure for time-profiled temporal association mining. Neural Computing and Applications, 32(21): 16337–16365.

[26] Nofong, V.M. (2016). Discovering productive periodic frequent patterns in transactional databases. Annals of Data Science, 3(3): 235–249.